The Missing Home Buyers: Regional Heterogeneity and Credit Contractions *

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Abstract

This paper studies how delayed home ownership from young buyers affects the transmission of shocks to housing markets. Using a panel of U.S. metro areas, I show that mortgage originations to young buyers have decreased more in regions with higher house prices over the past 15 years, despite credit standards varying only nationally. I develop and calibrate a regional business cycle model of the cross-section of housing markets consistent with these facts. Young buyers have more debt, and credit constraints bind more in high-price regions. Therefore an *aggregate* tightening of loan-to-value and payment-to-income requirements generates *heterogeneous* local responses in home ownership and prices. This channel explains 86% of the cross-sectional differences in originations and 50% of the differences in house price declines in 2007-12. Regional heterogeneity dampens the effect of subsidies like the First-Time Homebuyer Credit, because they fail to stimulate high-price regions which suffer the largest busts. Credit relaxation policies achieve larger stimulus and welfare gains.

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1 Introduction

A central feature of housing busts is their unequal incidence across demographic groups. During the largest U.S. postwar recessions, home ownership fell for young households, but not for older ones. The decline in young home ownership, a four decade-old trend, dramatically accelerated in 2007 and especially affected the Millennial cohort (Figure 1). It has attracted considerable attention from policymakers and the mortgage industry, as its effects on housing markets and buyers' welfare are still unclear.[1]

This paper studies how delayed home ownership from young buyers affects the transmission of local and aggregate shocks to housing markets. In particular, it seeks to explain how this decrease coincided with a large dispersion in house price busts between regions, a puzzling fact for simple models of asset market participation where entering buyers should arbitrage price differences away. Understanding the causes and effects of demographic and regional heterogeneity on housing markets is important, both because of their critical role for stimulus policies and the quantitative importance of young buyers.[2]

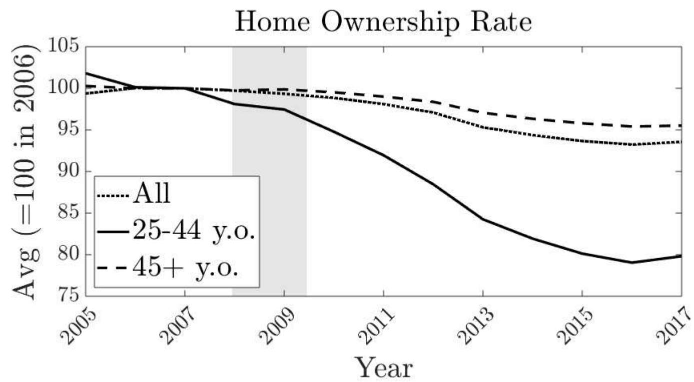
I show that delayed home ownership from young buyers is a channel which explains differences in housing busts between regions when credit contracts. Because young buyers tend to have lower income and little savings, they largely rely on mortgages when buying homes. Because they are more constrained in areas with higher house prices, they disproportionately respond to changes in credit standards by delaying home ownership. This, in turn, leads to larger price declines in those regions, dampening the effect of aggregate housing stimulus policies.

Using data on first-time buyers, I motivate this transmission channel by documenting two new facts on mortgage originations in a panel of U.S. metropolitan statistical areas (MSAs). First, mortgage originations to young buyers decreased by 40% more in high-price MSAs than in low-price MSAs in 2005-17, and house prices fell by four times more. Second, this has been the case despite credit standards varying only nationally over this period, with little regional variation in the characteristics of originated loans.

[1] Numerous examples include central banks ("Coming of age in the Great Recession", Federal Reserve Board speech by Gov. Lael Brainard, 2015), Government-Sponsored Enterprises ("Resolving the Millennial homeownership paradox", Fannie Mae, 2018), think tanks ("Millennial homeownership: Why is it so low and how can we increase it?", Urban Institute, 2018; "Are the kids alright? Saving and wealth accumulation among the Millennial generation", Brookings Institution, 2019), and banks ("Millennials: the housing edition", Goldman Sachs, 2014).

[2] See for instance Beraja, Hurst and Vavra (2019a) and Wong (2019) on the refinancing channel of monetary policy and Berger, Turner and Zwick (2019) on housing subsidies. In the Consumer Credit Panel of the New York Fed, first-time buyers represent about 50% of all purchase mortgages originated every year.

Figure 1: Changes in home ownership by age group



Notes: Values normalized to 100 in 2006 to view changes. Gray bands indicate NBER recessions. Source: American Community Survey.

I then develop an equilibrium regional business cycle model with housing markets consistent with these facts. Regions in the model differ in the amenity benefits that housing provides, the cost of residential investment and the price-elasticity of housing supply, and their exposures to nationwide income shocks. Each region is populated by overlapping generations of risk-averse households who face idiosyncratic income and mortality risks, and make discrete decisions on where to locate and whether to be renters or owners. When born, households also face different aggregate environments which cannot be insured away and reflect cohort-specific characteristics.

The key novel features are that (i) the regional distribution of house prices responds endogenously to local and aggregate shocks, and (ii) households sort across regions based on their individual characteristics.[3] Their interaction gives young buyers a pivotal role in the transmission of shocks to housing markets. Regional heterogeneity induces older and richer households to sort into high house price MSAs. Sorting, however, is limited by the low degree of regional mobility and the option to rent, which results in a large fraction of young and poor households living in high-price MSAs. Because of higher price levels, young households tend to delay home ownership and to be more credit-constrained when buying. As a result, a *nationwide* tightening of credit standards generates a *larger* drop in their home ownership in high-price regions than in low-price regions. In equilibrium, this leads to a larger price decline in high-price regions because the housing stock is durable and residential investment is irreversible.

[3]Existing regional business cycle models assume exogenous house prices and no household mobility (e.g. Hurst, Keys, Seru and Vavra (2016), Jones, Midrigan and Philippon (2018), Beraja et al. (2019a)). My paper is the first to solve for the evolution of the regional distribution of prices, bringing these models substantially closer to the data.

To discipline the degree of regional heterogeneity of the model, I map it to the panel of U.S. MSAs constructed in the empirical section. I estimate the parameters governing local housing market characteristics, and use it to quantify the effects of regional credit constraints on house prices and the transmission of stimulus policies. I develop a new solution method to compute the dynamics of the regional distribution of prices in response to unanticipated shocks. Using this framework, I obtain three results.

First, the transmission of aggregate credit shocks through young buyers explains 50% of the differences in house price declines between low and high price MSAs in 2007-12. A realistic *symmetric* tightening of loan-to-value (LTV) and payment-to-income requirements (PTI) replicates the 10% decrease in young home ownership in low price MSAs, and the 20% decrease in high price MSAs. It generates a 10% and a 20% decrease in house prices in these MSAs, versus 10% and 40% in the data.[4] More binding credit constraints lead to higher volatility in high price MSAs, a feature of the data which has been attributed to housing supply restrictions so far, but has remained puzzling for regions where such restrictions are unlikely to apply.[5] To illustrate the role of local house price levels for credit constraints, I study a counterfactual economy with the less heterogeneous regional house price distribution of 1997. The effect of regional credit constraints is muted: in response to the same credit contraction, the house price busts in the high and low price MSAs would have been of the same magnitude, and the aggregate bust would have been 3.8 percentage points (pp) smaller.

Second, I study the determinants of this transmission channel: first, the primitive parameters governing regional heterogeneity; then, the cohort-specific features of young buyers in the 2010s. I estimate that, once accounting for regional credit constraints, amenity differences contribute more to heterogeneity in housing busts than housing supply restrictions – in contrast to received wisdom.[6] Amenities generate larger differences in the static cross-section of house prices, which affect the extent to which credit constraints bind across MSAs.

I find that worse initial conditions have persistently lowered the home ownership rate of Millennials. I estimate that the negative effect on their earnings of graduating during the Great Recession has decreased their long-run home ownership rate by 5.8 pp, and

[4]In the last section of the paper, I show that these differences are further amplified by local shocks to labor income and to households' valuations for owner-occupied units.

[5]My explanation complements Nathanson and Zwick (2018), who focus on speculation in the "sand states" (Arizona, California, Florida, Nevada).

[6]For instance, the view that housing supply restrictions are key in generating dispersion in house price changes is central to the identification strategy in Mian and Sufi (2009).

that student debt has decreased it by 2 pp. Because of regional credit constraints, these effect are larger in high house price MSAs. In equilibrium, lower young home ownership in high-price MSAs decreases house prices (-8%) but boost rents (+8%), because buyers substitute from owner-occupied units to rentals.

However, I find that worse initial conditions have not affected the volatility of housing markets by making the Millennial cohort more sensitive to shocks. The neutral effect of initial conditions on the pass-through of shocks to prices results from two counterbalancing forces. On the one hand, they make buyers more likely to delay buying in recessions because they lower down payments and incomes, making LTV and PTI constraints more likely to bind. On the other hand, they result in lower long-run prices in the first place, making constraints less likely to bind. Thus the model demonstrates a dichotomy between the short-run and long-run objectives of stimulus policies targeting young buyers: ameliorating their balance sheets as they enter the housing market, for instance through student debt relief programs, would improve their home ownership level, but it would not make housing markets less volatile.

Third, I evaluate the implications of regional credit constraints for the transmission of housing stimulus policies. I study three policies targeting young buyers: (i) the First-Time Homebuyer Credit (FTHC), a temporary tax incentive of $8,000 implemented in 2008-10; (ii) a version of the FTHC where housing subsidies are indexed to local house prices; (iii) a credit relaxation policy. Table 1 summarizes their total welfare effects during the recovery of the 2010s, in terms of consumption-equivalent variations. To validate my results, I compare the treatment effects of the FTHC on home ownership and prices in the model to identified empirical estimates, and show that they closely align. The FTHC generates a persistent increase in aggregate welfare, due to improved access to home ownership and a small increase in non-durable consumption.[7] However, regional heterogeneity dampens its effectiveness, because a uniform subsidy fails to stimulate high-price MSAs, and thus has a limited aggregate effect. Intuitively, the same $8,000 dollar subsidy is more likely to relax buyers' credit constraints in low price MSAs where the average house price is $120,000, than in high price MSAs where it is $217,000. Furthermore, the timing of distortionary taxes used to finance the policy crucially affects the magnitude of the welfare gains, and can even reverse them entirely if taxes are raised during the recovery period, an effect from which local treatment effects in the empirical literature abstract.

Owing to these limitations, a place-based version of the FTHC where buyers get $12,000

[7] I show that these results are robust to allowing for mortgage default, another source of house price volatility which may have been suspected to dwarf the role of new buyers.

in high price MSAs and $4,000 in low price MSAs allows to almost double aggregate welfare gains, by better stimulating young home ownership in high-price MSAs for the same dollar cost. Finally, of the three policies, a relaxation of credit standards for new buyers during the recovery achieves the largest welfare gains. This policy replicates the 5 pp increase in maximum PTI requirements that Fannie Mae introduced in the summer 2017. It is a Pareto improvement, partly because it needs not be financed with distortionary taxes. Its large welfare gains, expected to persist up to the early 2020s, come from the fact that it directly relaxes credit constraints, and therefore does not rely on comparing the dollar value of subsidies relative to the levels of local prices.

Table 1: Welfare gains from three stimulus policies targeting young buyers

	FTHC	Place-based FTHC	PTI relaxation
Total welfare gain	+2.61%	+4.03%	+6.05%

Notes: Welfare gains are measured in terms of consumption-equivalent variations (CEVs, in terms of the consumption of one four-year period). CEVs are computed individually for every household type, each period during the transition. They are aggregated using the time-varying cross-sectional distribution of households, and summed across periods to obtain total welfare gains over the transition.

Related Literature

The analysis of the interaction of demographic characteristics and markets goes back to Malthus (1798), and to Mankiw and Weil (1989) for the housing market. Recently, Glover, Heathcote, Krueger and Ríos-Rull (2017) and Wong (2019) have studied the effect of recessions and of monetary policy on young buyers, while Ortalo-Magné and Rady (2006) have demonstrated their contribution to aggregate house price volatility in a stylized model. My contribution is to use a *spatial* setting to show that the larger effect of housing busts on young buyers amplifies regional heterogeneity during recessions, and dampens the transmission of stimulus policies. In particular, I contribute to three strands of the literature on regional heterogeneity and housing.

First, the large regional heterogeneity in house prices changes is the basis for many identification strategies in the empirical literature. For instance, Mian, Rao and Sufi (2013) show that falling housing net worth negatively affected households' consumption, and Mian and Sufi (2014) that it led to lower employment. Guren, McKay, Nakamura and Steinsson (2018) do a similar exercise over a longer horizon. On firms' side, Stroebel and Vavra (2019) use these variations to study their effects on retail prices. Many of these analyses rely on variations in local housing supply elasticities (Saiz (2010)) to instrument for prices, implicitly adopting the view that supply restrictions are the main determinants of house price changes differentials across regions. Much of the real estate literature shares this view, with which Davidoff (2013) disagrees for the housing cycle of the 2000s. My paper proposes a complementary explanation for regional differences in house prices changes. It relies on the extent to which housing *demand* is constrained across regions because of static differences in house prices largely due to amenities. I show that the large volatility in young buyers' mortgage originations in high price MSAs, despite identical regional variations in mortgage characteristics, lends empirical support to this explanation. I share my focus on young buyers with a recent empirical literature studying young home ownership during the 2010s, of which Acolin, Bricker, Calem and Wachter (2016), Bleemer, Brown, Lee, Strair and van der Klaauw (2017), Goodman and Mayer (2018), and Isen, Goodman and Yannelis (2019) are recent examples.[8] I share my focus on regional heterogeneity and the mortgage sector with Piskorski and Seru (2018), Gertler and Gilchrist (2018), and Gilchrist, Siemer and Zakrajsek (2018).

Second, my paper fits in the literature on regional housing markets and business cycles. Hurst et al. (2016) show that symmetric mortgage spreads across regions redistribute resources to riskier regions and stabilize the economy in downturns. Beraja et al. (2019a) demonstrate that regional heterogeneity in house prices dampens the refinancing channel of monetary policy. Based on differences between regional and aggregate responses to shocks, Beraja, Hurst and Ospina (2019b) advocate the use of a structural model of U.S. regions to draw inference about the drivers of business cycles. Jones et al. (2018) emphasize regional credit limits as drivers of fluctuations, a view that my paper adopts. My contribution to this literature is to endogenize the distribution of regional house prices and allow for sorting across regions. Lustig and Van Nieuwerburgh (2010) demonstrate that the level of house prices affects households' ability to borrow and insure against local shocks through LTV constraints. I reverse their perspective, and show that different house prices generate different binding constraints, which result in more heterogeneous responses during recessions. While my paper focuses on changes between regions during the bust, Landvoigt, Piazzesi and Schneider (2015) study changes within a region during the boom, and show that a relaxation in credit led cheaper housing segments to appreciate

[8] Hurst (2017) and Foote, Loewenstein and Willen (2019) also stress the role of young buyers during the Great Recession, and mention that they can potentially explain why the interpretations of the housing bust by Mian and Sufi (2009) and Adelino, Schoar and Severino (2016) diverge. A separate literature on family dynamics studies the trend towards low young home ownership, e.g. Fisher and Gervais (2011).

more. Finally, while several papers study monetary policy in regional models, my paper instead analyzes housing subsidies and credit relaxation policies. Berger et al. (2019) conduct an empirical analysis of the FTHC, and Auclert, Dobbie and Goldmsith-Pinkham (2019) study debt relief policies.

Third, I contribute to the real estate and urban economics literature studying the determinants of regional house prices, starting with Rosen (1979) and Roback (1982). Glaeser and Gyourko (2005) show how amenities and supply constraints explain long-run differences in regional prices when housing is modeled as a durable good. Glaeser, Gyourko and Saiz (2008) and Saiz (2010) show how differences in the price-elasticity of supply affect the volatility of prices across regions. Mayer (2011) points to supply restrictions as a prominent explanation for the volatility of historically cyclical regions, but notes that it fails to explain the volatility of elastic regions in the 2000s, for which Nathanson and Zwick (2018) provide an explanation based on speculation. Closer to the demand-side channel that I propose, Van Nieuwerburgh and Weill (2010) relate the rising dispersion in local house prices to the increase in regional income inequality. Like Guerrieri, Hartley and Hurst (2013), I stress the role of amenities in driving not only house price levels, but also their variations.

More broadly, my paper relates to the literature on durable goods and housing, recent examples of which include Berger and Vavra (2015), Justiniano, Primiceri and Tambalotti (2019), Favilukis, Ludvigson and Van Nieuwerburgh (2017), Kaplan, Mitman and Violante (forthcoming), and Garriga, Manuelli and Peralta-Alva (2019b). I extend it by showing how regional heterogeneity affects the transmission of subsidy and credit policies.

Outline

The rest of the paper is organized as follows. Section 2 presents new facts on mortgage originations to young buyers, and shows motivating evidence for the transmission mechanism formalized by the model. Section 3 presents the model, and Section 4 describes how it is mapped and calibrated to the panel of metro areas constructed in the empirical section. Section 5 studies the transmission of aggregate credit shocks through young buyers, and Section 6 studies the determinants of this mechanism. The implications for stimulus policies are studied in Section 7, and Section 8 concludes.

2 Mortgage Originations Across U.S. Regions

This section documents two new facts on mortgage originations to young buyers. First, over the past 15 years, mortgage originations to first-time buyers have decreased by 40% more in high-price MSAs than in low-price MSAs. Second, this has been the case despite mortgage underwriting standards varying nationally over this period, with little variation in the characteristics of originated loans across regions.

2.1 Data Description

I construct an annual panel dataset of U.S. metropolitan statistical areas from 2001 to 2017 by merging data on mortgage origination, households' demographics and house prices from four main sources. I use it to document stylized facts in this section, and later to calibrate the model.

I aggregate the data at the MSA level, the closest equivalent to local labor markets in these datasets.[9] Most weighted averages are computed using local population sizes as weights, sometimes loan sizes. All nominal variables are expressed in 1999 dollars using the BLS chained Consumer Price Index for all urban consumers.

First-time mortgage origination First, I use mortgage data on first-time purchase mortgages from the Federal Reserve Bank of New York Consumer Credit Panel (CCP). The CCP is an individual-level, 5% random sample of the U.S. population with credit files derived from Equifax. I use a representative 0.1% extract of this sample, with information on the number and balances of mortgages originated for all households and by age, aggregated at the MSA level. The data has information on 370 of the 384 MSAs in the U.S. In the CCP, a first-time buyer is defined as the first appearance of an active mortgage since 1999 with no indication of any prior closed mortgages on the borrower's credit report. Because first-time buyers are overwhelmingly young households, using this variable allows to uniquely study the mortgages of young buyers by merging the CCP with other loan-level datasets which do not have buyer's age as a variable. First-time buyers are quantitatively important: they represent 50% of purchase mortgages, and have volatile mortgage originations. Those fell by 46% in 2004-11, as much as for repeat-buyers.[10]

[9] An alternative would be to construct variables at the Commuting Zone level using indications on zip codes when they are available in the data. However this is not always the case.

[10] The flow of loans originated to first-time buyers at the peak of the housing cycle in 2005 was 1.417 million, 665,000 at the trough in 2011, and 1.059 million in 2017.

Loan underwriting standards Second, I combine the Single Family Loan-Level dataset from Freddie Mac and the Single Family Loan Performance dataset from Fannie Mae, to obtain information on the characteristics of loans issued to first-time buyers. I use the loan origination and acquisition data to focus on originations. The Government-Sponsored Enterprises loans (GSE) represent a subset of all purchase loans originated, but they were the primary source of mortgage securitization for first-time buyers during the 2010s. I focus on LTV and DTI ratios at origination, and borrower's credit score. The total stocks of loans are respectively 26.6 and 35 millions.

Household demographics Third, I use demographic information from the American Community Survey (ACS) of the U.S. Census Bureau. I use information on MSA-level total population, homeownership, age structure, migration flows, employment status and median income by age at the household level.

House prices Fourth, I use Zillow's Home Value Index (ZHVI) and Rental Index (ZRI) for all homes and at the MSA level, as measures of median house prices and rents.[11] The data being monthly, I annualize it by taking the unweighted average across months in a given year. The ZHVI is available from 2005 to 2017. The ZRI is available after 2010; I extrapolate values from 2005 to 2010 by assuming that rents in each MSA grew at the same rate as the U.S. consumer price index for rents from the BLS.[12]

2.2 Sorting Regions by House Price Levels

I start by sorting MSAs in two groups based on the level of house prices in 2006. In the empirical and the model sections, I keep this classification of MSAs fixed, and study the behavior of various variables within these two groups (e.g. the flow of mortgage originations). I denote MSAs in the bottom 50% of the distribution as "low-price MSAs" (in blue in maps, graphs, and tables), and those in the top 50% as "high-price MSAs" (in red); aggregate values are in black. This procedure is similar to Gertler and Gilchrist (2018), who sort them by the severity of the local house price contraction after 2007. In fact, these two classifications produce similar groups of MSAs, as many high price MSAs had larger

[11] I experimented with repeat-sale house price indexes like the All-Transactions House Price Index of the US Federal Housing Finance Agency and the S&P CoreLogic Case-Shiller Home Price Index. I obtained similar results for the regional distribution of prices.

[12] Consumer Price Index: Rent of Primary Residence in U.S. City Average, All Urban Consumers, Index 2010=100, Annual, Not Seasonally Adjusted.

busts (and larger booms). Importantly, my results do not rely on the choice of the date at which MSAs are sorted. Sorting them with the levels of 1997 house prices delivers identical results. This reflects the fact that some MSAs are historically more cyclical, and tend to have higher prices (Mayer (2011)). My mechanism contributes to explaining why this is the case.

A detailed description of these MSA groups is in Appendix A.3. Figure 15 plots them on a map and Table 11 lists them. Low-price MSA are concentrated inside the country (for instance Indianapolis, IN, and Memphis, TN). High-price MSA are concentrated in coastal regions and the Southwest (for instance Miami-Fort Lauderdale-Miami Beach, FL, Phoenix-Mesa-Glendale, AZ, and San Francisco-Oakland-Fremont, CA). The first group includes regions with historically stable house prices, with little construction restrictions, and in low demand from buyers. The second group includes regions with a historically higher volatility, which tend to have scarce buildable land, and regions with historically stable prices which experienced high volatility during the 2000s. All regions in the second group are in high demand from buyers.

Figure 14 in Appendix plots the evolution of the cross-section of house prices from 1997 to 2017. In 1997 the average price was \$70,000 in the bottom 50% of the distribution, and \$120,000 in the top 50%. They increased less in low-price MSAs and more in high-price MSAs during the boom (up to \$110,000 and \$240,000), and respectively fell less and more during the bust (down to \$80,000 and \$160,000). Because high price regions have more expensive homes and a large population, aggregate value- and population-weighted price indexes (including median prices) track this group more closely. This will be the case in the model too when aggregating MSAs.

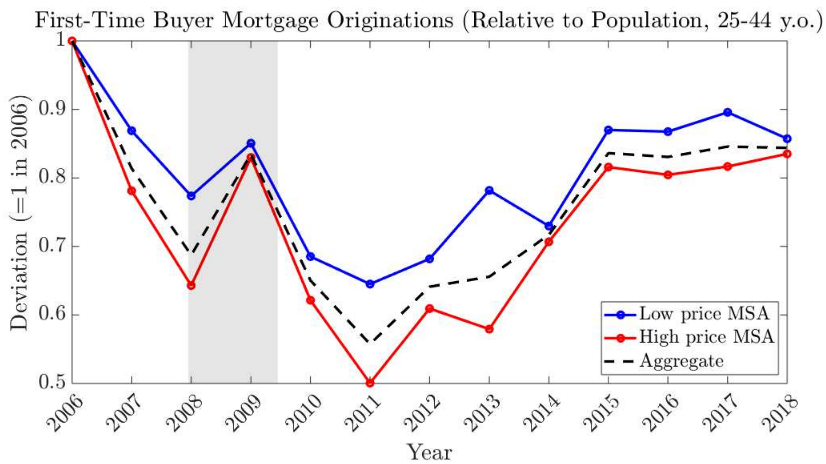
House price differences induce sorting between the two MSA groups. High-price MSAs have a 50% larger population, because they are on average more attractive and productive (Mayer (2011)). However, sorting is limited. Despite house prices being 100% higher, income in high-price MSAs is 10%-30% higher (median and average), and the shares of young households (25-44 years old) and home ownership rates are identical (ACS data). This is key for the transmission of credit shocks because it implies that buyers have higher debt to income ratios in high-price MSAs.[13]

[13]Other housing characteristics are similar, and thus unlikely to affect sorting between the two groups of MSAs. The types of housing units are similar, and their sizes are only slightly lower in the more urban high-price MSAs. The distribution of households by age and tenure status across unit types, number of bedrooms, and building age is similar too (Appendix A.4). Relatedly, Sinai (2012) argues that demand fundamentals account only for a small fraction of cross-sectional differences in housing busts.

2.3 Mortgage Originations to First-Time Home Buyers

Mortgage originations After sorting MSAs into low- and high-house price regions, I document a first fact: mortgage originations to first-time buyers have decreased more in high-price MSAs over the past 15 years after the recession. Figure 2 plots changes in the average flow of purchase mortgages originated to first-time buyers (normalized by local population) by region type and in aggregate. Averages are population-weighted.[14]

Figure 2: Mortgage originations to first-time home buyers by region

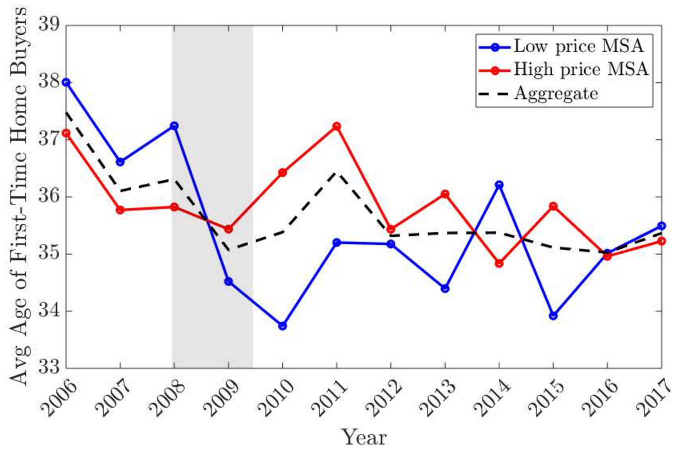


Notes: The solid lines depict changes in the average flow of mortgages originated to first-time buyers in low- (blue) and high-price MSAs (red), relative to their populations. The dashed line depicts the economywide average. To view changes, their values are normalized to 1 in 2006. Gray bands indicate NBER recessions. Source: CCP/Equifax, Zillow.

Delaying homeownership The decrease in first-time mortgage originations was associated with a temporary increase in the average age of first-time buyers in high price MSAs, suggesting that many buyers delayed home ownership in unaffordable areas when credit contracted (Figure 3). These findings complement Berger and Vavra (2015), who show that buyers' propensity to adjust housing vary over time. Here, I show that this margin depends on local prices, and thus substantially varies across space.

[14] This result is robust to weighting by the inverse of population of the total and of the young population, to account for the larger population size of high price MSAs. It can also be seen by plotting the flow of mortgages originated directly (Appendix A.6).

Figure 3: First-time home buyer age by region



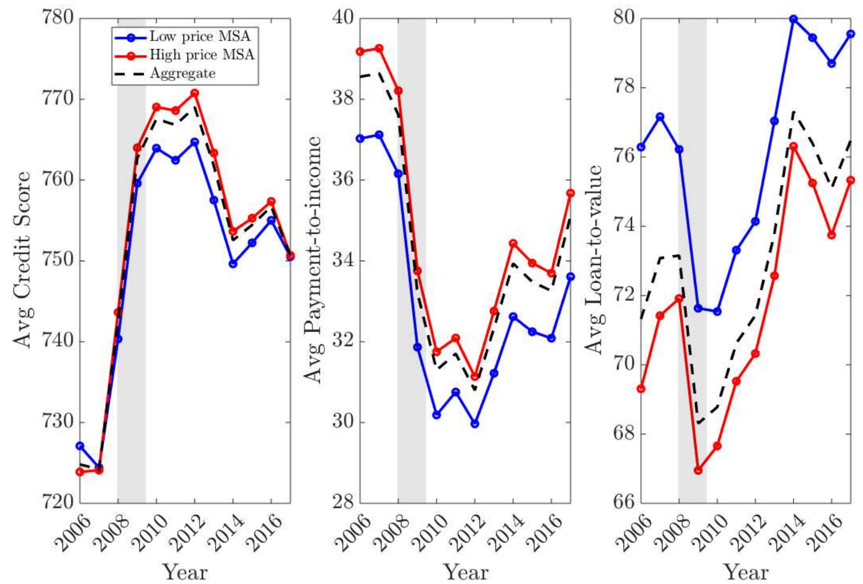
Notes: The solid lines depict the average age of first-time buyers in low- (blue) and high-price MSAs (red). The dashed line depicts the economywide average. It is calculated as a weighted average using the number of loans at each age. Results are similar when inversely weighting by the shares of each age groups in the MSA population (in the ACS), to account for changes in the age structure of population across MSAs. Gray bands indicate NBER recessions. Source: CCP/Equifax, Zillow.

Rising dispersion in young home ownership The decrease in first-time mortgage originations resulted in a decrease in the entry rate into homeownership. It led not only to a nationwide decrease in homeownership rates, which is well documented (Garriga, Eubanks and Gete (2018)), but also to an increase in their dispersion across MSAs for young households (Figure 23 in Appendix).

2.4 Nationally Varying Credit Standards

What accounts for the large regional dispersion in mortgage originations to young buyers? The second fact that I document is that there has been little regional differences in how credit standards have changed across MSAs over the last 15 years. Instead, as Figure 4 shows, credit scores, LTV, and PTI requirements tend to vary at the national level. This finding is reminiscent of Hurst et al. (2016), who have documented the lack of spatial variation in GSE mortgage spreads, despite observable regional heterogeneity. While I am only able to show this fact in the Fannie Mae and Freddie Mac data, it is likely to apply to all first-time buyers, as the GSEs and the Federal Housing Administration have dominated the mortgage landscape since the recession. This findings also complement Greenwald (2018) by showing how LTV and PTI ratios lack spatial variation across space.

Figure 4: Average credit score, payment-to-income, and loan-to-value ratios at origination across regions



Notes: Left panel: The solid lines depict the average credit score of first-time buyers in low- (blue) and high-price MSAs (red), when their mortgages were first originated. The dashed line depicts the economywide average. Middle panel: average payment-to-income ratio. Right panel: average loan-to-value ratio. Gray bands indicate NBER recessions. Source: Fannie Mae, Freddie Mac, Zillow.

2.5 Other Sources of Variations in Home Ownership

The symmetric tightening of credit constraints across MSAs, and the heterogeneous responses in the flow of mortgages originated (hence in young home ownership), are key features of the data that my model will replicate. Appendix A.7 discusses alternative explanations for these changes, including mortgage default, local credit supply shocks, and the collapse of the private label mortgage securitization market.

2.6 Intuition: Regionally Binding Credit Constraints

I conclude the empirical section with a back-of-the-envelope calculation which illustrates the mechanism that I formalize in the model. The mechanism incorporates the two facts that I have documented: a *symmetric* tightening of credit standards across regions generates a *larger* decrease in mortgage originations (hence in young home ownership) in MSAs with higher house prices. Therefore these MSAs experience larger price declines in equilibrium. The core of the mechanism is that credit constraints bind more in high-price than in low-price MSAs.

Consider the following calculations. Denote the mortgage rate as r^b, the loan maturity as n, and LTV and PTI requirements by θ_{LTV} and θ_{PTI}. A simple mortgage payment formula implies that the maximum loan size imposed by the PTI constraint is

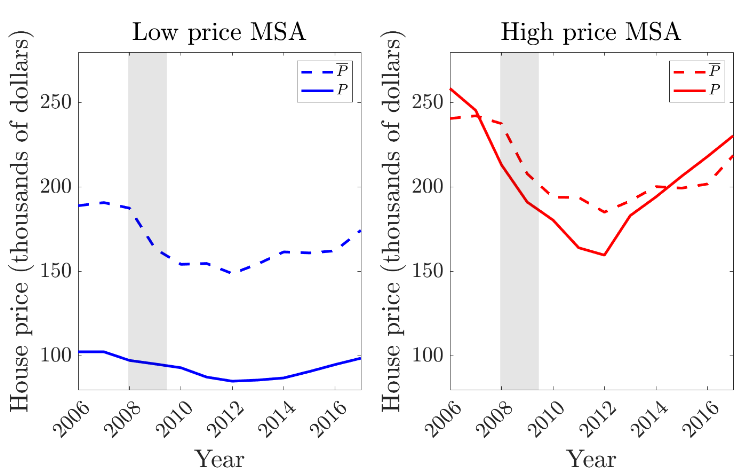
$$\text{PTI max loan size} = \frac{1-(1+r^b)^{-n}}{r^b} \underbrace{\theta_{PTI} Y}_{\text{max payment each period}}. \tag{1}$$

By definition, the maximum LTV loan size is $\theta_{LTV} \times$ price. Therefore the maximum house price that households can afford is

$$\text{max affordable price } \overline{P} = \min \left[\frac{1-(1+r^b)^{-n}}{r^b} \theta_{PTI} Y + \text{down}, \frac{\text{down}}{1-\theta_{LTV}} \right]. \tag{2}$$

Figure 5 plots the maximum affordable price and the actual house price in each region, feeding in time series for the empirical counterparts of the variables in Equation 2. While the constraints are slack in low-price MSAs in 2006-17, they are clearly binding in high-price MSAs. A decrease in the maximum affordable price is therefore associated with a decrease in the actual price. However, these calculations abstract from many important dimensions for housing markets, such as heterogeneity in households' incomes and down payments, the option to rent, the sorting of households' across regions, and the interplay of local and aggregate shocks. I therefore turn to a structural model of regional housing markets to formalize and quantify this mechanism.

Figure 5: Regional credit constraints: maximum affordable price ($\overline{P}$) vs. actual price (P)



Notes: Left panel: actual price (solid line) and maximum affordable price $\overline{P}$ (dashed line) in high price regions. Right panel: same variables for low price regions. $\overline{P}$ is calculated using the formula in the main text, using $r^b = 5\%$ (mortgage rate), $n = 30$ years (loan maturity), and the path of average PTI ratios and median income in each group of MSAs (ACS data). Gray bands indicate NBER recessions. Nominal variables are expressed in 1999 dollars.

3 Regional Business Cycle Model with Housing Markets

This section constructs a regional business cycle model of the cross-section of housing markets. Its key novel feature is that the *dynamics* of the regional distribution of house prices and rents is endogenous. I develop a tractable numerical method to exactly calibrate this class of models, and solve for price trajectories in response to unanticipated local and aggregate shocks.

3.1 Environment

The economy consists of two building blocks. First, two sets of regions, low- and high-price MSAs ($j = L, H$), are connected by migrations. Regional housing markets differ in the amenity benefits they bring to households, the cost of residential investment, and the price elasticity of housing supply. In this section, local labor markets are identical, and households receive a stochastic endowment stream subject to idiosyncratic and aggregate shocks (the latter are zero in steady state). In the last section, I extend the model to allow regional endowment processes to differ in their exposures to aggregate income shocks.

Second, each set of regions nests a Bewley-Huggett-Aiyagari incomplete markets, heterogeneous agents economy. The economy is populated by overlapping generations of households with a life-cycle. Population size is stationary, and there is a continuum of measure 1 of households. Time is discrete.

Preferences Households have time- and state-separable preferences. They have a constant relative risk aversion (CRRA) utility function over a constant elasticity of substitution (CES) aggregator of nondurable consumption c_t and housing services h_t. Amenity benefits are modeled as additive utility shifters χ_j, which depend on households' regions. A household's instantaneous utility function in region j is

$$\frac{u\left(c_t, h_t\right)^{1-\gamma}}{1-\gamma} + \chi_j = \frac{\left[\left((1-\alpha)c_t^{\epsilon} + \alpha h_t^{\epsilon}\right)^{\frac{1}{\epsilon}}\right]^{1-\gamma}}{1-\gamma} + \chi_j. \tag{3}$$

Homeowners can own only one home, in a single size which delivers a fixed flow of services $\overline{h}$. Renters consume continuous quantities of housing services h_t. χ_j captures the amenities accruing with different locations and the quality of the local housing stocks. Bequests are accidental and not chosen by households, but there is a warm-glow bequest motive captured by the function

$$U(b) = \frac{\psi b^{1-\gamma}}{1-\gamma}. \tag{4}$$

For simplicity, bequests are a normal good, redistributed equally to all newborns.

Households' choices Households can be either owners or renters. In each region, the rental and the owner-occupied housing markets are partially segmented in that they give access to different housing sizes. Owner-occupied units come in a single size $\overline{h}$ at price p_j in region j, and rental housing for type j can be chosen continuously in $\left[\underline{h}, \overline{h}\right]$ at the rent R_j, with $\underline{h}$ being the minimum size. Every period, households can move between metro areas, in which case they incur additive moving costs in terms of utility, m. They also choose nondurable consumption c_t, savings in one-period risk-free bonds or long-term mortgage debt b_t. They inelastically supply one unit of labor to the local labor market.

Endowments and risk Households face idiosyncratic income risk, and mortality risk. The survival probabilities $\{p_a\}$ vary over the life-cycle. The law of motion for the log income of a working-age household i, of age a, in region j is:

$$\begin{aligned} y_{i,j,a,t} &= g_a + e_{i,t} + \beta_j \eta_{US,t} \\ e_{i,t} &= \rho_e e_{i,t-1} + \varepsilon_{i,t} \\ \varepsilon &\overset{iid}{\sim} \mathcal{N}\left(\mu_\varepsilon, \sigma_\varepsilon^2\right) \end{aligned} \tag{5}$$

g_a is the logarithm of their deterministic life-cycle income profile. $e_{i,t}$ is the logarithm of the idiosyncratic, persistent component of income for household i. It has the same persistence in the two regions.[15] $\eta_{US,t}$ is the aggregate component of regional income, which is zero in steady state. β_j is the sensitivity of income in region j to aggregate income $\eta_{US,t}$. In the main version of the model $\beta_j = 1$ for all j. In the last section $\beta_H > 1 > \beta_L > 0$.

The income process $Y_{i,j,a,t} = \exp(y_{i,j,a,t})$ is supermodular in regional and individual income. The cross-derivatives

$$\frac{\partial^2 Y_{i,j,a,t}}{\partial \left(\beta_j \eta_{US,t}\right) \partial g_a}, \frac{\partial^2 Y_{i,j,a,t}}{\partial \left(\beta_j \eta_{US,t}\right) \partial e_{i,j,t}} > 0 \tag{6}$$

create a complementarity between the regional component, and the life-cycle and stochas-

[15] The assumption of identical local income processes can be easily relaxed.

tic components of individual income. Over the transition (when $\eta_{US,t} \neq 0$), it creates a motive for higher income households to live in regions with higher average income, generating spatial sorting.

Absent heterogeneity in β_j, spatial sorting arises because of amenity differences. The concavity of u makes it more costly for poorer households to sacrifice non-durable consumption to enjoy better amenities in regions with higher house prices. This is a key difference with urban economics models with risk-neutral households, which abstract from wealth effects.

Taxes and transfers Labor income is subject to the progressive tax and transfer schedule of Heathcote, Storesletten and Violante (2017),

$$T(Y) = Y - \varphi Y^{1-\tau}, \tag{7}$$

where τ and φ respectively control the progressivity and level of taxes.

Retirement income is given by the pension schedule of Guvenen and Smith (2014), which replicates salient features of the U.S. pension system (see Section B.1 in Appendix).

Households' balance sheets Markets are incomplete, as households only have access to a one-period risk-free bond with an exogenous rate of return $r > 0$ to smooth consumption, and to houses.

Renters who are inactive face a no-borrowing constraint. Renters who buy can use long-term mortgages to borrow, subject to LTV and PTI constraints, which only apply at origination. They face an exogenous, kinked interest rate schedule, which makes borrowing more costly, and comes from an unmodeled fixed financial intermediation wedge: $\tilde{r}_t = r^b > r$ if $b_t < 0$, otherwise $\tilde{r}_t = r$. Because $r^b > r$, indebted households never simultaneously hold risk-free assets and debt, and prefer paying off their mortgages first. The assumption that owners cannot save accounts for the large fraction of "wealthy hand-to-mouth" households with little liquidity in the data (Kaplan and Violante (2014), Gorea and Midrigan (2018)).

Mortgages are non-defaultable. In Section 7.4, I extend the model to allow households to default on non-recourse mortgages, to capture the exit margin of homeownership. When making this change, I assume that houses used as collaterals return to the market upon default, that defaulters incur a utility penalty d, are forced to rent in the same region, and return to the owner-occupied market in the next period with probability 1.[16] Finally, owners cannot refinance and extract housing equity. [17]

Cohort-specific initial conditions In the simulation, all agents enter the economy as renters. They are divided into two categories based on the period in which they are born, to capture cohort-specific features which affect housing markets. Households becoming active on the housing market prior to 2005 draw a level of initial wealth equal to the average bequest in the economy, and their initial income from the stationary distribution. Households who become active after 2005 – Millennials – have two distinct features. First, their levels of initial wealth are lower by a fixed amount corresponding to student debt payments in the first three periods of their lives (from their twenties to their early thirties). Second, when born during a recession, they draw their initial income from a distribution which is first-order stochastically dominated by the baseline distribution, such that that the recession has a negative, long-lasting effect on their earnings.

Housing supply The housing stock $H_{j,t}$ in region j, in square feet, depreciates at rate δ:

$$H_{j,t} = (1-\delta)H_{j,t-1} + I_{j,t} \tag{8}$$

Residential investment $I_{j,t}$ compensates for depreciation. At the household level, owners pay a maintenance cost in dollars at the beginning of each period, $\delta p_j \overline{h}$.

The construction sectors in the two regions produce according to a reduced-form upward-sloping supply curve,

$$I_{j,t} = \overline{I}_j p_{j,t}^{\rho_j} \tag{9}$$

The housing supply elasticity ρ_j, and the constraints on residential investment $\overline{I}_j$ differ across regions. The lower ρ_j, the larger the price movements required to induce the same change in residential investment in percentage terms. The lower $\overline{I_j}$, the higher the price level required to induce the same level of residential investment. Since households supply labor inelastically, the construction sectors are only affected by price changes.[18]

Finally, the markets for owner-occupied housing and for rentals are segmented. Every period, the housing stock $H_{t,j}$ (in square feet) is exogenously divided into a fractions ho_j^{sqft} of owner-occupied houses, and a fraction $1 - ho_j^{sqft}$ of rentals, with no endogenous

[16]In the model, this corresponds to a 4-year. It is also straightforward to allow for a different probability.

[17]I will consider this option in an extension.

[18]It is straightforward to allow for time-varying region-specific shifters $\overline{I}_{j,t}$, to capture regions' different cyclical sensitivities orthogonal to prices.

conversion from one to the other. Appendix B.2 discusses this assumption in detail. As a result, the supply of owner-occupied houses and of rentals (in square feet) are respectively equal to

$$H^{o}_{j,t} = ho_j^{sqft} H_{j,t} \quad \text{and} \quad H^{r}_{j,t} = \left(1 - ho_j^{sqft}\right) H_{j,t} \tag{10}$$

Timing A household in region j makes a discrete tenure and location choice, then earns labor and financial income in its region of origin, and makes consumption, savings or debt, and housing choices. I now turn to describing the households' problem recursively.

3.2 Household's Problem

The household's individual state variables are its tenure status r, o (renter or owner), location $j = L, H$ (low-price or high-price region), age a, assets or debt b, and endowment y. In the interest of space I only describe the problems of households in the low-price region (L). The problem is similar for the high-price region H.

3.2.1 Renter

Denote the value function of a renter of age a, with savings b_t and income y_t, who starts the period in region L, as $V^{rL}(a, b_t, y_t)$. First, a renter chooses the location where it will move over the period, and whether to rent or own in its new location. The envelope value of the value functions for each option is:

$$V^{rL}(a, b_t, y_t) = \max\left\{V^{rL,rL}, V^{rL,rH}, V^{rL,oL}, V^{rL,oH}\right\} \tag{11}$$

Denote $d_{rL} \in \{rL, rH, oL, oH\}$ the resulting policy function for the discrete choice problem. After, renters choose their nondurable consumption, housing services, and savings, or mortgage debt if they borrow to purchase a house.

First, the value of being inactive and staying a renter in region L is given by the Bellman equation

$$V^{rL,rL}(a, b_t, y_t) = \max_{c_t, h_t, b_{t+1}} \frac{u\left(c_t, h_t\right)^{1-\gamma}}{1-\gamma} + \chi_L + \beta\left(p_a \mathbb{E}_t\left[V^{rL}(a+1, b_{t+1}, y_{t+1})\right] + (1-p_a) U_{t+1}\right), \tag{12}$$

subject to the constraint that expenses on nondurable consumption, rented housing services, and savings, must be no lower, and at the optimum equal to, resources from labor income net of taxes and transfers, and financial income from risk-free assets

$$c_t + R_{L,t}h_t + b_{t+1} = y_t - T(y_t) + (1+r)b_t, \tag{13}$$

and to a no-borrowing constraint on assets, as well as a constraint on the size of rental housing

$$b_{t+1} \geq 0, \quad h_t \in \left[\underline{h}, \overline{h}\right]. \tag{14}$$

Expectations are taken with respect to the conditional distribution of idiosyncratic income at date t. Since the household does not own a house, the warm-glow bequest motive is over its financial wealth, $U_{t+1} = \frac{\psi b_{t+1}^{1-\gamma}}{1-\gamma}$.

Second, when moving to region H and staying a renter, a household incurs a moving cost m in utility terms and faces the continuation value function in region H:

$$\begin{aligned}
&V^{rL,rH}(a,b_t,y_t) = \max_{c_t,h_t,b_{t+1}} \frac{u(c_t,h_t)^{1-\gamma}}{1-\gamma} + \chi_L - m + \beta\left(p_a \mathbb{E}_t\left[V^{rH}(a+1,b_{t+1},y_{t+1})\right] + (1-p_a)U_{t+1}\right)\\
&\text{s.t. } c_t + R_{L,t}h_t + b_{t+1} = y_t - T(y_t) + (1+r)b_t\\
&b_{t+1} \geq 0, \quad h_t \in \left[\underline{h}, \overline{h}\right]
\end{aligned} \tag{15}$$

Third, when buying a house in the same region, the renter's value is

$$V^{rL,oL}(a,h_t,b_t,y_t) = \max_{c_t,h_t,b_{t+1}} \frac{u(c_t,h_t)^{1-\gamma}}{1-\gamma} + \chi_L + \beta\left(p_a \mathbb{E}_t\left[V^{oL}(a+1,b_{t+1},y_{t+1})\right] + (1-p_a)U_{t+1}\right). \tag{16}$$

In addition to rental services purchased at rate $R_{L,t}$, the household buys owner-occupied housing at price $p_{L,t}$,

$$c_t + R_{L,t}h_t + F_m + p_{L,t}\overline{h}(1+f_m) + b_{t+1} = y_t - T(y_t) + (1+r)b_t, \quad h_t \in \left[\underline{h}, \overline{h}\right], \tag{17}$$

using a mix of savings accumulated over the life-cycle, and of long-term mortgage debt b_{t+1} borrowed at rate r^b, subject to fixed and proportional origination fees F_m and f_m, and to LTV and PTI constraints,

$$b_{t+1} \geq -\theta_{LTV}\, p_{L,t}\overline{h} \quad \text{and} \quad b_{t+1} \geq -\frac{\theta_{PTI}}{\left(1+r^b-\tilde{\theta}\right)} y_t. \tag{18}$$

θ_{LTV} is the maximum fraction of the house price in region L which the household can borrow, so $1-\theta_{LTV}$ is the down payment requirement. θ_{PTI} is the maximum fraction of its income that a household is allowed to spend on mortgage payments each period. These constraints only apply at origination, and may be violated in subsequent periods in response to income shocks and house price movements. Every period, homeowners with a mortgage pay interests and roll over their current debt subject to the requirement that they repay a fraction $1-\tilde{\theta}$ of the principal,

$$b_{t+1} \geq \min\left[\tilde{\theta} b_t, 0\right]. \tag{19}$$

The lowest payment that households can make in a period therefore equals $\left(1+r^b-\tilde{\theta}\right) b_t$. The LTV constraint directly restricts the maximum mortgage balance of a buyer. By imposing a limit on the mortgage payment, the PTI constraint limits the maximum mortgage balance b_t of a buyer given its current income. Together, they restrict the maximum prices for owner-occupied units that buyers can afford. If house prices differ between regions, buyers' location choices may be constrained by mortgage credit, and credit movements will have larger effects on buyers' choices in regions where these constraints are more binding. As a result, regional credit constraints will affect macroeconomic dynamics.

Finally, the household's bequest motive now includes housing wealth, $U_{t+1} = \frac{\psi\left((1+r^b)b_{t+1}+p_{L,t}\overline{h}\right)^{1-\gamma}}{1-\gamma}$.

Fourth, the value of moving to region H and buying a house is similar, with the addition of the moving cost m:

$$V^{rL,oH}(a,b_t,y_t) = \max_{c_t,h_t,b_{t+1}} \frac{u\left(c_t,h_t\right)^{1-\gamma}}{1-\gamma} + \chi_L - m + \beta\left(p_a \mathbb{E}_t\left[V^{oH}(a+1,b_{t+1},y_{t+1})\right] + (1-p_a)U_{t+1}\right), \tag{20}$$

subject to the budget and borrowing constraints

$$\begin{aligned} &c_t + R_{L,t}h_t + F_m + p_{H,t}\overline{h}(1+f_m) + b_{t+1} = y_t - T\left(y_t\right) + (1+r)b_t, \\ &b_{t+1} \geq -\theta_{LTV}\, p_{H,t}\overline{h} \quad \text{and} \quad b_{t+1} \geq -\frac{\theta_{PTI}}{\left(1+r^b-\tilde{\theta}\right)} y_t. \end{aligned} \tag{21}$$

3.2.2 Home Owner

The home owner's problem shares the same structure as the renter's. Denote the value function of a home owner starting the period in region L as as $V^{oL}(a,b_t,y_t)$. First, it chooses to either remain an owner or sell its house and become a renter, and the region where it moves over the period.

$$V^{oL}(a, b_t, y_t) = \max\left\{V^{oL,oL}, V^{oL,oH}, V^{oL,rL}, V^{oL,rH}\right\} \tag{22}$$

Denote the resulting policy function for the discrete choice problem as $d_{oL} \in \{oL, oH, rL, rH\}$. In the last section I allow for default, and the envelope value also includes the value of the default option $V^{oL,d}$.

First, the value of being inactive and staying a home owner in region L is given by the following Bellman equation with fixed housing services $\overline{h}$:

$$V^{oL,oL}(a, b_t, y_t) = \max_{c_t, b_{t+1}} \frac{u\left(c_t, \overline{h}\right)^{1-\gamma}}{1-\gamma} + \chi_L + \beta\left(p_a \mathbb{E}_t\left[V^{oL}(a+1, b_{t+1}, y_{t+1})\right] + (1-p_a)U_{t+1}\right), \tag{23}$$

subject to a budget constraint including a proportional maintenance cost $\delta p_{L,t}\overline{h}$

$$c_t + b_{t+1} + \delta p_{L,t}\overline{h} = y_t - T\left(y_t\right) + (1+\tilde{r})b_t, \tag{24}$$

as well as a loan amortization constraint described earlier,

$$b_{t+1} \geq \min\left[\tilde{\theta} b_t, 0\right]. \tag{25}$$

If the household has mortgage debt, the interest rate is $\tilde{r} = r^b$, otherwise the interest rate on risk-free assets is $\tilde{r} = r$. The bequest motive includes housing wealth in the same region, $U_{t+1} = \frac{\psi((1+r^b)b_{t+1} + p_{L,t}\overline{h})^{1-\gamma}}{1-\gamma}$.

Second, when selling its house and purchasing a house in the other region H, an owner incurs a moving cost m and enjoys the amenity benefits of the new region χ_H:

$$V^{oL,oH}(a, b_t, y_t) = \max_{c_t, b_{t+1}} \frac{u\left(c_t, \overline{h}\right)^{1-\gamma}}{1-\gamma} + \chi_L - m + \beta\left(p_a \mathbb{E}_t\left[V^{oH}(a+1, b_{t+1}, y_{t+1})\right] + (1-p_a)U_{t+1}\right) \tag{26}$$

The new house is purchased with a mix of housing equity, savings in risk-free bonds (if it holds no debt), and a new mortgage b_{t+1}, subject to the same origination fees and borrowing constraints as a renter first purchasing a house, and selling transaction costs f_s

as well as maintenance costs $\delta p_{t,L}\overline{h}$ on its current house,

$$
\begin{aligned}
&c_t + F_m + p_{H,t}\overline{h}(1+f_m) + b_{t+1} = y_t - T\left(y_t\right) + (1+\tilde{r})b_t + \left(1 - f_s - \delta\right) p_{L,t}\overline{h}, \\
&b_{t+1} \geq -\theta_{LTV} p_{H,t}\overline{h} \quad \text{and} \quad b_{t+1} \geq -\tfrac{\theta_{PTI}}{\left(1+r^b-\tilde{\theta}\right)} y_t.
\end{aligned}
\tag{27}
$$

Third, an owner selling its house and becoming a renter in the same region incurs the proportional selling transaction cost f_s and the maintenance cost $\delta p_{L,t}\overline{h}$:

$$
V^{oL,rL}(a, b_t, y_t) = \max_{c_t, b_{t+1}} \frac{u\left(c_t, \overline{h}\right)^{1-\gamma}}{1-\gamma} + \chi_L + \beta\left(p_a \mathbb{E}_t\left[V^{rL}(a+1, b_{t+1}, y_{t+1})\right] + (1-p_a) U_{t+1}\right), \tag{28}
$$

subject to the budget and no-borrowing constraints

$$
\begin{aligned}
&c_t + b_{t+1} = y_t - T\left(y_t\right) + (1+\tilde{r})b_t + \left(1 - f_s - \delta\right) p_{t,L}\overline{h}, \\
&b_{t+1} \geq 0
\end{aligned}
\tag{29}
$$

Because the owner sells its house overt the period, the bequest motive only includes financial wealth, $U_{t+1} = \frac{\psi\left((1+r)b_{t+1}\right)^{1-\gamma}}{1-\gamma}$.

Fourth, the value of selling its house to move and become a renter in the other region H is identical, with the addition of the moving cost m.

3.3 Equilibrium

This section defines a spatial recursive competitive equilibrium. The next section studies the evolution of the regional distribution of house prices in response to unanticipated aggregate shocks.

Definition 1 (Spatial recursive competitive equilibrium)**.** Given exogenous time paths for $\{\eta_{US,t}, \theta_{LTV,t}, \theta_{PTI,t}\}$, an equilibrium consists of, for region $j = L, H$ and home ownership status $k = r, o$:

(i) sequences of prices $\left\{P_t^j, R_t^j\right\}$,

(ii) of value functions $\left\{V_t^{jk}, V_t^{j'k'}\right\}$,

(iii) of policy functions $\left\{d_t^k, c_t^k, h_t^k, b_{t+1}^k\right\}$,

(iv) a law of motion for the cross-sectional distribution of households $\lambda_t(j, ho, a, b, y)$ across regions, ownership statuses, and idiosyncratic states,

such that households optimize given prices, the law of motion for the distribution of households' is consistent with their choices and with prices, and markets clear (see below).

Housing market clearing There are four market-clearing conditions. The market-clearing conditions for owner-occupied housing in regions $j = L, H$ are

$$\int_{\Omega_t^{oj}} \overline{h} d\lambda_t = \underbrace{pop_{j,t} \times ho_{j,t}^{hh} \times \overline{h}}_{\text{owner-occupied housing demand in } j} = \underbrace{ho_j^{sqft} \times H_{j,t}}_{\text{owner-occupied housing supply in } j} \tag{30}$$

The market-clearing conditions for rentals in regions $j = L, H$ are

$$\underbrace{\int_{\Omega_t^{rj}} h_{j,t} d\lambda_t}_{\text{rental demand in } j} = \underbrace{\left(1 - ho_j^{sqft}\right) \times H_{j,t}}_{\text{rental supply in } j} \tag{31}$$

$pop_{j,t} = pop_j(\mathbf{P_t}, \mathbf{R_t})$ denotes the population share and $ho_{j,t}^{hh} = ho_j^{hh}(\mathbf{P_t}, \mathbf{R_t})$ the homeownership rate in region j at date t. $\Omega_t^{oj} = \Omega^{oj}(\mathbf{P_t}, \mathbf{R_t})$ and $\Omega_t^{rj} = \Omega^{rj}(\mathbf{P_t}, \mathbf{R_t})$ are the sets of households who are owners and renters in region j at date t. In equilibrium, these objects depend on the vectors of prices and rents in the two sets of regions because of spatial sorting.

Steady state In steady state, the housing supply schedule in region j is

$$H_j = \frac{I_j}{\delta} = \frac{\overline{I}_j}{\delta} p_j^{\rho_j} \tag{32}$$

3.4 Model Solution

I develop a tractable solution method to exactly calibrate this class of spatial models and solve for the dynamics of the regional distribution of prices and rents. It exploits the single housing size $\overline{h}$ and the homogeneity in p_j of the housing supply function. Details are in Appendix B.4.

3.5 Discussion

This section discusses the main assumptions and properties of the model.

Sorting: amenities Differences in amenity benefits (χ_j) attract households to better regions. This is a key ingredient of real estate models, going back to models of compensating differentials (Rosen (1979), Roback (1982)). They account for all unmodeled features which make locations H more attractive. In equilibrium, higher local housing demand, combined with more expensive construction ($\bar{I}_H$) and a lower price-elasticity (ρ_H), lead to higher prices in high amenity regions.[19] Higher prices lead to sorting of richer households into high amenity regions, because it is less costly for them than for poorer households to sacrifice nondurable consumption to enjoy higher amenities, because of the concavity of u. The fact that the marginal buyer is richer further contributes to higher prices.

In the data and the calibrated model, there is less sorting by income and wealth *between* regional housing markets than across market segments *within* a single region (Landvoigt et al. (2015)). My model reflects the fact that average house prices (across housing types) are higher in high-price MSAs. Households born into unaffordable regions may move to affordable regions. But they will choose to stay if the regional price difference is low relative to the cost of moving. As a result, many households will be credit-constrained in high-price regions. This, in turn, makes them more sensitive to credit contractions.

Sorting: local income In the extended model of Section 7.4 with regional exposures to aggregate income, the complementarity between the regional and the individual components of income create an additional motive for sorting. The supermodularity of the income process in its various components is a feature of Bewley-Huggett-Aiyagari models with log income processes. Higher income and older workers have an incentive to locate in regions with higher average income. When the economy is hit by a negative shock with a larger effect on the high price region ($\beta_H > \beta_L$), the incentive for richer households to stay in those regions decreases, leading some of them to migrate to the low price region, amplifying the decrease in local prices in their region of origin, and dampening it in their region of destination. An alternative would be to assume different average productivities across regions, $\mu_H > \mu_L$, which would generate additional sorting.[20]

[19] These parameters are jointly estimated. See the calibration section.

[20] In that case, lower amenity differences would be needed to match regional differences. But provided that the model matches income differences in the data (which it does), the effect of shocks on regional prices would be the same, because regional credit constraints would be as likely to bind.

Migrations Households migrate both in steady state and in response to shocks. In steady state, amenity differences are the only motive for migrations. When born into a given region, as they experience deterministic and stochastic income variations, households may be misallocated geographically and chose to migrate (e.g. to cheaper MSAs if local prices are too high for them). In recessions, households migrate to regions where income decreases less, and where housing becomes endogenously more affordable.[21]

Risk aversion First, risk aversion amplifies the decrease in house prices when the economy is hit by a negative shock, as households require a larger discount to hold owner-occupied houses. Long-term mortgages which must be amortized every period create a "consumption commitment" (Chetty and Szeidl (2007)). Households are more reluctant to make it when risk aversion is high and income is persistently low, since it makes consumption smoothing harder.

Second, risk aversion interacts with the location choices of households. It makes the consumption commitment associated with mortgage payments especially strong in high price MSAs. It induces more sorting by income, as it makes homeownership riskier given idiosyncratic income risk.[22] The option of migrating partly alleviates this commitment by allowing households to move to regions where housing is less expensive. [23,24]

4 Calibration and Model Evaluation

This section describes the calibration and shows that the model replicates key features of housing and mortgage markets, both in the aggregate and in the cross-section of MSAs.

[21] An alternative would be to assume that households are also hit by exogenous moving shocks (Krivenko (2019)). This assumption may be less realistic for regional housing markets than for housing types within regions. Furthermore, the calibrated model matches average migration flows and profiles by age without such shocks. The steady state net migration rate is zero because the model is stationary, but the gross migration rate is positive.

[22] This is reminiscent of Sinai and Souleles (2005) for rents.

[23] This form of migratory insurance coming from house price levels complements the migration motive of Blanchard and Katz (1992) based on labor market differences. Glaeser (2008) and Notowidigdo (2019) provide empirical evidence showing that some households migrate to weaker labor markets to enjoy lower costs of living, and Bilal and Rossi-Hansberg (2019) build on this result.

[24] In section 7.4, mortgage default is another form of insurance which is partly a substitute to the migration option. With non-recourse mortgages, the option to default may help owners smooth consumption. When risk aversion is low, home owners tend to exercise both options more often, hold less liquid assets and more mortgage debt.

4.1 Calibration

Table 2 summarizes the calibration. Parameters are split into externally calibrated and internally calibrated parameters, and into aggregate and regional parameters. A period in the model represents 4 years. Average worker income Y is normalized to 1 to convert model values in dollars.

Mapping the model to regional data I use the panel of MSAs constructed in Section 2 to discipline the calibration of the model. Regions are split into two groups: regions with ex ante lower prices ("Region L", in blue), and regions with ex ante higher prices ("Region H", in red).

External Parameters The following parameters are externally calibrated.

Preferences. The instantaneous utility function u is CES. The elasticity of substitution is set to 1.25 based on the estimates of Piazzesi, Schneider and Tuzel (2007). The weight α on housing services is endogenously chosen to match an average rent to average income ratio of 0.20 as measured in the Consumer Expenditure Survey (including utilities).

Labor income process. I assume a persistence of 0.6867, and a standard deviation of 0.3868, standard values for an income process at a four-year frequency. Those numbers are implied by the annual estimates of Floden and Lindé (2001).

Regional business cycle sensitivity In Section 7.4, $\beta_H = 1.75 > \beta_L = 0.27$. To obtain these values, I estimate the elasticity of median local income to U.S. regional income by MSA using a panel of MSAs from the County Business Patterns over the 2005-2017 period. Estimates are then matched with my dataset, and averaged by region groups using population sizes as weights. These estimates incorporate the feedback from house prices to labor income (Mian et al. (2013), Mian and Sufi (2014)).[25]

Housing supply elasticity. Merging the data from Saiz (2010) and averaging using population sizes as weights, I set $\rho_L = 2.7$ and $\rho_H = 1.8$.

Housing depreciation. I restrict the depreciation rates δ to be equal across regions, and equal to an average 2.39% per year, equal to the average depreciation rate for privately-held residential property in the BEA Fixed Asset tables for the period 1972-2016.

Mortgages. The mortgage rate is $r^b = 0.050$, equal to the average 30-Year Fixed Rate Mortgage Rate in the U.S. prior to the boom-bust episode of the 2000s (Freddie Mac, Primary Mortgage Market Survey) minus the CPI inflation (BLS).

[25] This approximates a fully specified model with labor supply and nominal wage rigidities.

Table 2: Calibration

Parameter	Explanation	Value	Source/Target
	External: aggregate		
γ	Risk aversion	2.000	Standard
ϵ	CES parameter housing/consumption	0.2	Elasticity of substitution=1.25
ρ_e	Autocorrelation income	0.914	Floden and Lindé (2001)
σ_ε	Std. dev. income	0.097	Floden and Lindé (2001)
$\underline{Y}$	Income floor	0.100	Guvenen and Smith (2014)
b_0	Student debt	see text	New York Fed
$F_{y_0}(.)$	Initial dist. graduating in recession	see text	Kahn (2010)
r^b	Mortgage rate	0.050	Pre-boom real 30-year FRM
$\tilde{\theta}$	Mortgage duration	0.969	Gorea and Midrigan (2018)
f_s	Transaction cost selling	0.060	Kaplan et al. (forthcoming)
F_m	Fixed mortgage origination fee	0.006	Kaplan et al. (forthcoming)
f_m	Proportional mortgage origination fee	0.008	Kaplan et al. (forthcoming)
δ	Housing depreciation/maintenance	0.015	Kaplan et al. (forthcoming)
	External: regional		
ρ_L, ρ_H	Housing supply elasticity	2.700,1.800	Saiz (2010)
	Internal: aggregate		
β	Discount factor	0.952	Wealth/income=4.4
α	Preference for housing services	0.400	Rent/income=0.20
ι	Mortgage spread	0.006	Leverage=0.37
θ_{LTV}	Max. LTV ratio	0.900	Top LTV distribution
θ_{PTI}	Max. PTI ratio	0.580	Top PTI distribution
m	Utility cost of moving	2.750	Avg moving rate L,H=1.7%
τ	HSV tax/transfer progressivity	0.290	Avg mgl tax rate=33%
φ	HSV tax/transfer level	0.900	Net taxes/income=0.10
ψ	Bequest motive level	0.200	Bequest/income=0.05
$\underline{b}$	Bequest motive homotheticity	0.001	Normal good
	Internal: regional		
$\overline{I_L}, \overline{I_H}$	Size residential investment	0.048,0.014	$P_L = \$120K, P_H = \$217K$
χ_L, χ_H	Amenity benefits from owner-occupied housing	2.461,2.969	$P_L/R_L = 9, P_H/R_H = 15$
ho_L^{sqft}, ho_H^{sqft}	Fraction owner-occupied sqft	0.841, 0.857	Avg homeownership L,H=67%

Notes: One period in the model is four years. Parameters and targets are annualized. Sources: The pre-boom 30-year fixed rate mortgage rate is from Freddie Mac's Primary Mortgage Survey. The wealth/income ratio is obtained by scaling the value of 1.45 from Gorea and Midrigan (2018) for the bottom 80% of households (SCF), by the ratio of housing-income in my data relative to theirs. Leverage is measured as total mortgage debt outstanding to housing wealth, using the levels of home mortgages outstanding and the levels of real estate at market value for households and nonprofit organizations from the Financial Accounts of the U.S. (Z.1., Federal Reserve Board). The average moving rate is from the ACS for 2011-2015 (annual rate), the average default rate in 2007 from RealtyTrac, the tax rate targets from Heathcote et al. (2017), the bequest targets from Straub (2019), house prices and rents from Zillow and the ACS (in 1999 dollars), and homeownership rates from the ACS, the average rent/average income ratio is from the CEX (including utilities).

The amortization $\widetilde{\theta}$ is chosen such that the fraction of the principal to be repaid each period, $1-\widetilde{\theta}$, is 6.4%, the four-year equivalent of the value reported by Greenwald, Landvoigt and Van Nieuwerburgh (2018).

The proportional transaction cost of selling a house of $f_s = 0.060$, the fixed and proportional mortgage origination fees of $F_m = \$1,200$ and $f_m = 0.008$ are taken from Kaplan et al. (forthcoming) and Gorea and Midrigan (2018).

Risk aversion. I set $\gamma = 2$, a standard value in the macro-finance literature. I later do a robustness exercise where I solve the model for higher values, which amplify my results.

Student debt. Bleemer et al. (2017) show that student debt decreases young homeownership. I model it as negative lump-sum transfer which lowers the initial asset positions of households entering the economy after 2005 in the first three periods of their lives (from 21 to 32 years old), by $40,000 dollars. This is about the average student debt level of $38,390 in 2018 (source: Federal Reserve Bank of New York).[26]

Graduating in a recession. Kahn (2010) estimates that a 1 pp increase in unemployment during a recession leads to 2.5-10% lower wages 15 years later for the cohorts that graduated during the recession.[27] I use these estimates to calibrate the initial income distribution for $\{e_0\}$ from which households born during the Great Recession draw. In 2008-10, the unemployment rate rose by 5 pp from 5% to 10%. Extrapolating the lower bound of those estimates implies that earnings for this cohort should be about $5 \times 2.5\% = 12.5\%$ lower 15 years later than they would have been, had they not graduated in 2008-10. I choose the average of the distribution of $\{e_0\}$, $\mu_{e_0} = -0.20$ to match this fact when simulating a panel of those households.[28]

Internal parameters: aggregates The following parameters are chosen to match aggregate moments.

Discount factor. β is chosen to match a ratio of aggregate wealth to aggregate income

[26] See also "Student Loan Debt Statistics In 2018: A $1.5 Trillion Crisis", *Forbes*, June 13, 2018.

[27] An IV estimator finds a 10% decrease while an OLS estimator finds a 2.5% decrease. Most interpretations tend to favor the OLS estimator to capture broader effects on cohorts' earnings that may be omitted by local treatment effects.

[28] In the transition, the persistence of the income process will generate a decrease in total income because of the lower initial mean of households born in 2008, even without an explicit negative aggregate income shock. When doing the main experiment, I choose the path of aggregate income $\{\eta_{US,t}\}$ as a residual, to replicate the decrease in total income in 2007-12, given the decrease which results from the 2008 cohorts graduating in the recession.

of 4.4.[29,30] Note that because of mortality risk, the effective discount factor is $p_a \beta$.

Mortgage spread. $\iota = r^b - r$ is chosen to match aggregate leverage, measured as total mortgage debt outstanding to housing wealth. I respectively use the levels of home mortgages outstanding and of real estate at market value for households and nonprofit organizations from the Financial Accounts of the U.S. (Z.1., Federal Reserve Board), and calculate that this ratio was equal to 0.37 in 2005. It implies a value for the rate of return on assets of $r = 0.044$, relatively close to the mortgage rate. It can be interpreted as the rate of return on a bundle of liquid assets, which would include both low return bonds and higher return stocks, as in Favilukis and Van Nieuwerburgh (2018).

Credit standards. The maximum loan to value $\theta_{LTV} = 0.900$ and the maximum payment to income $\theta_{PTI} = 0.580$ are chosen to match the 90th percentiles of the LTV and PTI distributions among mortgagors (Kaplan et al. (forthcoming) and Greenwald (2018)).

Mortgage default. In the in the last section, households can default on their mortgages, which are assumed to be non-recourse. The default cost $d = 0.75$ is chosen to match the average foreclosure rate of 0.2% in the cross-section of MSAs in 2005 (RealtyTrac data)

Taxes and transfers. I calibrate τ and φ in the Heathcote et al. (2017) schedule, $T(Y) = Y - \varphi Y^{1-\tau}$, to respectively match the progressivity and level of the tax system (Y is pre-tax earnings). The income-weighted marginal tax rate is 0.33, and I target a ratio of government expenditures to income of 0.10. Net taxes are used to finance wasteful government expenditures that do not affect households' choices. This delivers $\tau = 0.29$, close to the authors' estimate, and $\varphi = 0.90$. I also impose a minimum income level equal to 10% of average income, a standard value.

Bequests. The warm-glow bequest motive ψ is chosen to match the ratio of average bequests to average income of 0.05 reported by Straub (2019).

Internal parameters: regions The remaining parameters are calibrated to match regional moments, which are key for the sensitivity of local housing markets to shocks.

Housing markets. Amenity benefits χ_j, supply constraints $\bar{I}_j$, and the shares of owner-occupied square feet ho_j^{sqft} in regions $j = L, H$ are jointly estimated to match the regional

[29] This value, lower than the value of 5.6 in the Survey of Consumer Finances (SCF) data, is obtained by focusing on the bottom 80% of the distribution of households, since my model lacks a mechanism to generate high income inequality at the top, such as heterogeneity in discount factors or "superstar" income levels. I calculate this value by scaling the value of 1.85 reported by (Gorea and Midrigan, 2018) by the ratio of housing wealth to income in my model relative to theirs, to ensure that this moment is consistent with house price levels in the panel data that I use for the rest of the calibration.

[30] There is little high quality data on household wealth at the regional level. If this data was available, I would directly use it to calibrate the wealth to income ratio in my regional panel.

distribution of prices, price to rent ratios, and homeownership rates. I find that:

(1) The amenity benefits from owning in Region H are 40% higher than in Region L. Higher amenities create an incentive for households to locate in these regions, and in turn result in higher local prices through endogenous sorting of buyers by income and wealth.

(2) It is 3 times more costly for the construction sector to produce the same square footage of housing in region H than in Region L.[31] This is consistent with those regions having more stringent geographic and population constraints in the data.

(3) The fraction of *square footage* devoted to owner-occupied units is similar in the two regions, around 80%. This number reflects the fact that home ownership rates among *households* are similar across regions, around 66%, and the fact that owner-occupied units tend to be larger than rentals.[32]

Migrations. I use detailed data from the ACS on migrations between all pairs of metro areas to compute an annual gross migration rate of 1.6% between the low- and high-price regions.[33] The model generates the same value with $m = 4$. A relatively high cost is needed to prevent households from arbitraging house price and amenity differences between regions and moving too much over their life-cycles relative to the data. These high costs are a reduced form device for mechanisms reducing migration which are explicitly modeled e.g. in Kaplan and Schulhofer-Wohl (2017) and Karahan and Rhee (2019). [34]

4.2 Model Evaluation: Aggregates and Regional Heterogeneity

4.2.1 Housing and Mortgage Markets

The model successfully replicates key moments of housing and mortgage markets in the data. Table 3 shows aggregate moments targeted by the calibration, obtained by aggregating household-level variables using the 2005 cross-sectional distribution of households'

[31] Inverting the reduced-form residential investment function, the cost of producing one sqft of housing is $\left(\frac{1}{\overline{I}_L}\right)^{\frac{1}{\rho_L}}$ in Region L, and $\left(\frac{1}{\overline{I}_H}\right)^{\frac{1}{\rho_H}}$ in Region H.

[32] Absent a full housing ladder, the model slightly overstates the ratio of sizes of owner-occupied units to rentals relative to the data, which slightly biases the estimates of ho_j^{sqft} upwards.

[33] I use the Metro Area-to-Metro Area In-, Out-, Net, and Gross Migration table, which is data aggregated for the 2012-2016 period. I merge it with my panel to obtain a cross-section of MSA pairs. The corresponding survey question asks respondents whether they have lived in the same MSA for a year or moved from another MSA.

[34] The average interstate migration rate has trended downwards since the early 1990s, without significant changes during the Great Recession. However, the composition of migrations has slightly changed during the 2010s. When the economy is hit by the recession, there are small but significant population flows between regions, which result in a 2.5 pp increase in the population of Region L and a 1.7 pp decrease in the population of Region H (relative to trend), also close to the data.

locations, tenures, ages, income, and wealth. Table 4 shows that the model also matches the full distribution of LTV and PTI ratios, which is not targeted.

Table 3: Aggregate moments targeted by the calibration

Variable	Data	Model
Wealth/income	4.40	4.15
Avg. rent/ income	0.23	0.22
Leverage	0.37	0.32
P90 LTV	0.92	0.83
P90 PTI	0.58	0.56
Migration Rate	0.016	0.014

Sources: The wealth/income ratio is obtained by scaling the value of 1.45 from Gorea and Midrigan (2018) for the bottom 80% of households (SCF), by the ratio of housing-income in my data relative to theirs. Average rent to average income: CEX data (including utilities). Leverage is measured as total mortgage debt outstanding to housing wealth, using the levels of home mortgages outstanding and the levels of real estate at market value for households and nonprofit organizations from the Financial Accounts of the U.S. (Z.1., Federal Reserve Board). The average moving rate is from the ACS for 2011-2015. LTV ratios are from Kaplan et al. (forthcoming), PTI ratios from Greenwald (2018). Flow targets are annualized.

Table 4: Aggregate LTV and PTI distributions, not targeted by the calibration

	LTV		PTI	
	Data	Model	Data	Model
P10	0.19	0.26	–	0.08
P25	0.40	0.44	–	0.13
P50	0.64	0.62	0.36	0.28
P75	0.79	0.79	0.48	0.37
P90 (targeted)	0.92	0.83	0.58	0.56

Source: Kaplan et al. (forthcoming) and Greenwald (2018) .

The model generates a large heterogeneity in the cross-section of housing markets in line with the data. Table 5 shows that, by virtue of the solution method, the model exactly matches the cross-section of house prices, and almost exactly reproduces price to rent ratios and home ownership rates in the data. While not targeted, the house price to income ratio is much higher in high price regions than in low price regions. Importantly, regional differences in price to income ratios are largely driven by differences in prices, a sign of limited sorting.

Table 6 displays regional moments not targeted by the calibration. Despite the large heterogeneity in house price levels, the two groups of regions are relatively similar in terms of income. The model replicates the regional heterogeneity in income and popula-

Table 5: Regional moments targeted by the calibration

Variable	Data L	Model L	Data H	Model H
Homeownership rate	0.67	0.69	0.67	0.67
Price per unit ($)	120,370	120,370	217,100	217,100
Price/rent per sqft	9.00	10.04	15.00	13.05
Price/income (not targeted)	3.62	4.64	6.44	6.84

Sources: ACS, Zillow, BLS. Nominal variables are expressed in 1999 dollars.

tion sizes. In the data, median income is about 10% higher in high price regions, a value somewhat overstated by the model. In the model, households in high-price MSAs tend to accumulate more savings to meet larger down payment requirements, and have higher debt to income ratios. This results not necessarily in larger LTV ratios (since prices are higher and maximum LTVs are identical across regions), but in a distribution of PTI ratios more skewed to the right. When credit contracts, PTI constraints will bind for more households in high price MSAs. Limited sorting is also apparent in the regional life-cycle profiles of income, wealth, and migration rates (Appendix B.5).

Table 6: Regional moments not targeted by the calibration

Variable	Data	Model
Pop Share H/L	1.50	1.59
Income all hhs H/L	1.10	1.30

Sources: ACS.

Finally, the model generates close to the right fraction of home owners with a mortgage, but overstates the average size of owner-occupied units relative to rentals (Table 7). This is a consequence of the absence of a housing ladder, which Appendix B.3 further discusses.

Table 7: Aggregate moments not targeted by the calibration

Variable	Data	Model
Fraction homeowners with mortgage	0.66	0.57
Avg. size occupied/rented unit	1.50	2.28

Sources: Kaplan et al. (forthcoming).

5 Heterogeneous Responses to Aggregate Credit Shocks

This section presents the transmission mechanism of shocks through young buyers in the context of the 2007-09 credit contraction and the recovery of the 2010s. In the next section (6) I study its determinants, and in the last section (7) how it affects the transmission of stimulus policies.

These quantitative results are obtained by solving for the full nonlinear transition dynamics of the economy in response to unanticipated shocks to aggregate income $\{\eta_{US,t}\}$ and mortgage underwriting standards $\{\theta_{LTV,t}, \theta_{PTI,t}, F_{m,t}, f_{m,t}\}$. This is a challenging problem that involves solving for the paths of four prices $\{P_{L,t}, P_{H,t}, R_{L,t}, R_{H,t}\}$, which is made tractable by the method presented in Section B.4.

5.1 The Great Recession and the Housing Bust(s)

The recession is modeled as as sequence of unanticipated negative shocks to aggregate income and credit standards, fed to the model. One period is four years. $t = 0$ represents 2007, the period prior to the bust. (1) I choose $\{\eta_{US,t}\}$ in $t = 1, 2$ (2007-11 and 2012-15) to generate the same decrease in real income of 9.2% in 2011 and 1.8% in 2015 as in the data, relative to 2007. (2) I choose the maximum LTV and PTI constraints $\{\theta_{LTV,t}, \theta_{PTI,t}\}$ in $t = 1, 2, 3$ (2007-11, 2012-15 and 2016-19) to generate the 20% decrease in leverage in the data from 2007 to 2015. This requires a 19.50% decrease in the maximum LTV and a 49% decrease in the maximum PTI (from 90% to 72% and from 58% to 29%), numbers close to Kaplan et al. (forthcoming). At the same time, the fixed and proportional mortgage origination costs $\{F_{m,t}, f_{m,t}\}$ increase from \$1,200 to \$2,000 and from 0.60% to 1%, based on evidence in Favilukis et al. (2017).[35] Finally, I assume that the credit take one additional period, $t = 4$ (2020-23), to revert to zero, to reflect the tightness of mortgage credit in the 2010s (Goodman (2017)).

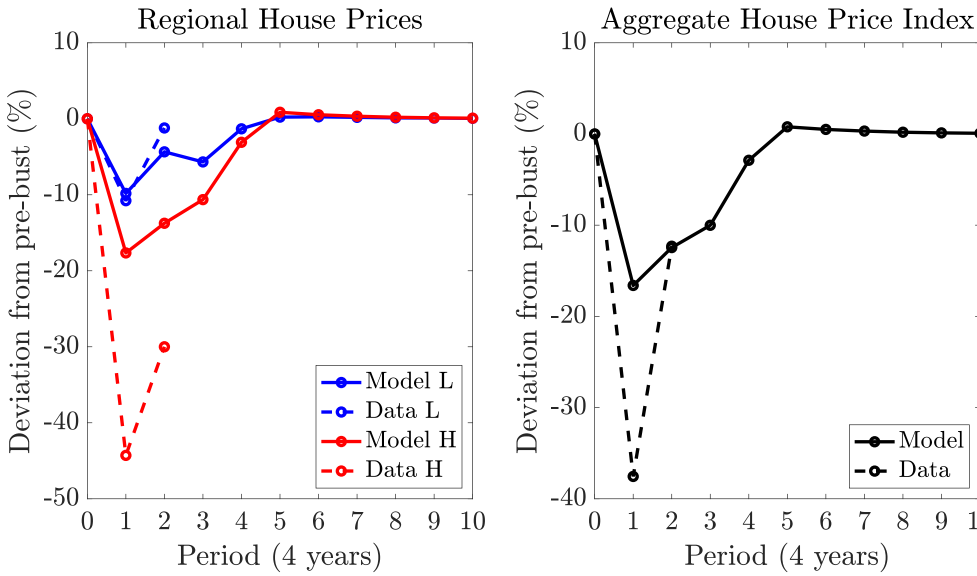
Figure 6 plots the response of regional and aggregate house prices. The model generates a large amount of heterogeneity in house price responses to the aggregate recession, despite the fact that regions are hit symmetrically.

Quantitatively, the model replicates the 10% price decrease in low-price MSAs (in blue), and replicates about half of the 45% price decrease in high-price MSAs (in red).

[35] Source for income data: Real Median Household Income in the United States, U.S. Census Bureau, Income and Poverty in the United States. Source for leverage data: aggregate leverage is measured as total mortgage debt outstanding to housing wealth in the Flow of Funds. I assume that θ_{LTV} and θ_{PTI} vary in the same proportion as in Kaplan et al. (forthcoming), in line with empirical evidence.

Constructing the aggregate house price index as a value-weighted index of regional prices, the model generates an 18% decrease in aggregate house prices, close to half of the 39% decrease in the data, mostly driven by the larger decrease in high-price MSAs.

Figure 6: Response of Regional and Aggregate House Prices to an Aggregate Recession



Data source: Zillow. Changes in percentage terms relative to the pre-bust period (2006).

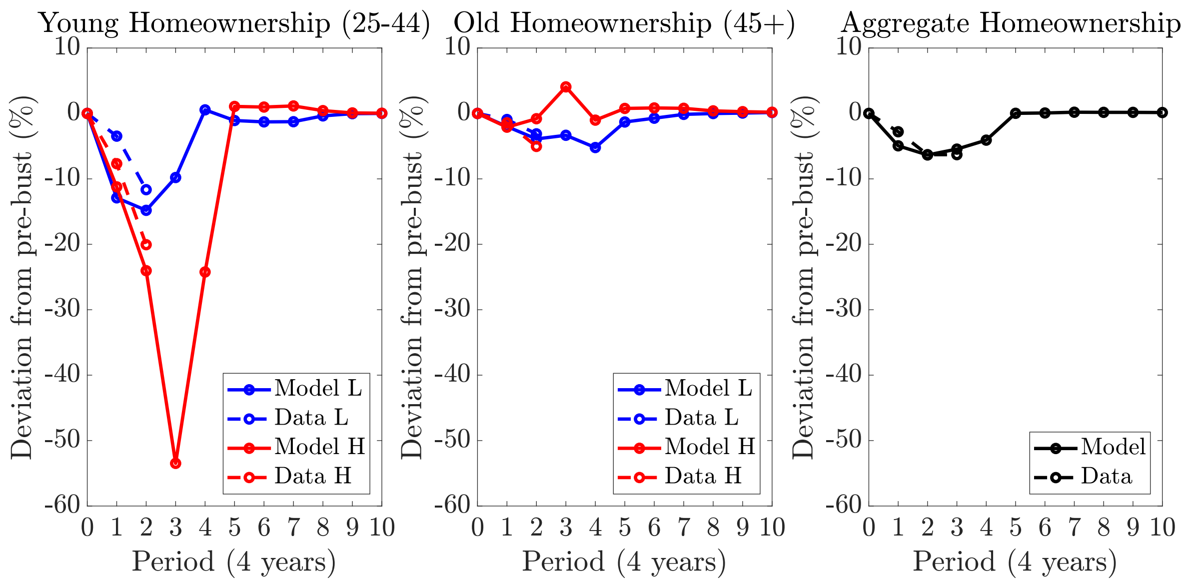
Delaying home ownership As in the data, Figure 7 shows that the recession generates a decrease in the home ownership rate of young households (25-44 years old), who rely more on credit to buy homes than older households who either already own a house or have accumulated more savings.[36] From 2006 to 2015, young home ownership decreases by 10% in Region L and by 20% in Region H. In contrast, the home ownership rate of older households stays stable. Nationwide, the model replicates the 7% decrease in average home ownership from peak (2007) to trough (2016), from 69% to 63.4%. Thus the model generates the decrease in the level, and the increase in the dispersion in young home homeownership rates in the data, consistent with Figure 3.

Substitution to rentals The recession generates a decrease in rents in the first period when the shock hits, but then a sustained *increase* in rents in both regions in the following periods, as in the data (Figure 28 in Appendix).[37] Three periods after the beginning of the

[36] In this version of the model, repeat buyers, who already own a home and are buying a new one, always buy in the other regions, since there is a single housing size by region.

[37] The model fails to generate an increase in rents in the first period when the shock hits.

Figure 7: Regional Homeownership Rates by Age



Data source: ACS. Changes in percentage terms relative to the pre-bust period (2006).

recession (in 2019), rents are 12% higher than in 2007 in Region L, and 7% higher in Region H. This is a general equilibrium response to lower income and tighter credit conditions, which lead young households to substitute to rentals, and is consistent with the empirical evidence of a rental boom during the recovery (Gete and Reher (2018)). [38]

5.2 Shock Contribution: *Where* PTI constraints bind is key

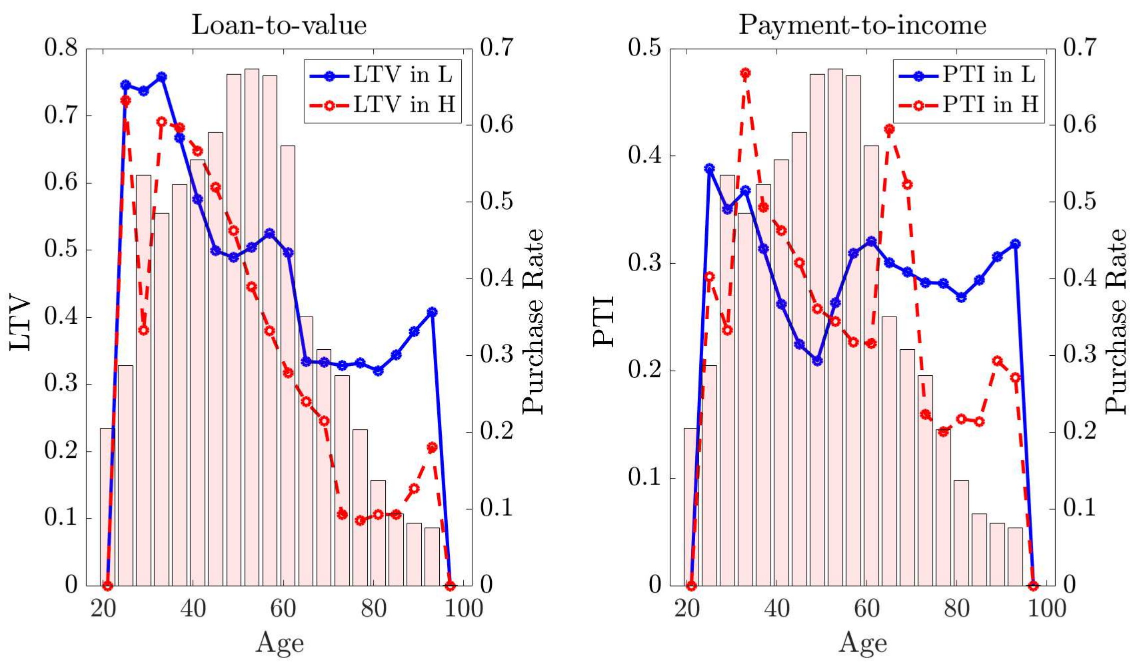
I now turn to decomposing the contributions of the income and credit shocks in explaining regional price responses to the Great Recession. Figures 29 and 30 in Appendix plot the responses of prices and rents in the low-price and in the high-price region for one shock at a time.

Credit standards Most of the level and dispersion in price responses is due to the tightening of PTI constraints. This is partly because the tightening of LTV requirements was smaller, but more importantly because the PTI constraint is more likely to bind for more households.

[38] An extension of the model which would allow for (even frictional) conversion from owner-occupied units to rentals would generate the boom in single and multifamily rental residential investment observed in the data, in part due to the entry of investors, as a result of the decrease in prices and the increase in rents (see e.g. Demers and Eisfeldt (2018), Mills, Molloy and Zarutskie (2019), and Garriga, Gete and Tsouderou (2019a)). The stronger quantity adjustment would imply weaker price adjustments.

Figure 8 shows that except for the youngest households, the life-cycle profile of LTV ratios is below LTV requirements during the recession ($\{\theta_{LTV,t}\}_{t=1}^{3} = 0.72$). In contrast, PTI ratios tend to be larger ($\{\theta_{PTI,t}\}_{t=1}^{3} = 0.29$). Furthermore, while the profiles of LTV ratios are similar across regions, the profiles of PTI ratios differ strongly at ages when the probability to buy a first home is the highest. At around age 30, payments to income are higher by up to 10 pp in the high-price MSA relative to the low-price MSA, as a result of higher prices and limited sorting.

Figure 8: Regional life-cycle profiles of LTV and PTI ratios, and renters' purchase rates



Notes: Model values obtained using the stationary distribution of households in 2005. Left panel: life-cycles of LTV ratio by region (left axis, blue and red solid lines) and life-cycle of probability that first-time buyers buy in high price regions (right axis, pink bars). Right panel: life-cycles of PTI ratio by region (left axis, blue and red solid lines) and life-cycle of probability that first-time buyers buy in high price regions (right axis, pink bars).

Income The income shock, in contrast, has little effect on house prices, a classical result in housing models (e.g. Favilukis et al. (2017), Kaplan et al. (forthcoming), Garriga and Hedlund (2017)).[39] Spatial equilibrium implies that in response to a symmetric income shock, prices decrease in the high-price region (-2%), but slightly increase (+0.5%) in the low-price region. This reaction is due to migrations, whereby young households

[39]To generate larger house price decreases in response to income shocks, an increase in income *risk*, especially left-tail risk, is often needed, and needs to be combined by a higher risk aversion or recursive preferences, in long-run risk models à la Bansal and Yaron (2005) .

in the high-price region "sell their location" by moving to regions where housing is less expensive.

The *directionally* different effect of the same income shock on regional prices is consistent with and complements the evidence on the "migration accelerator" (Howard (2019)). Not only do prices in the region of destination increase in response to in-migration, but prices also decrease in the region of origin. Migrations *amplify* regional differences in response to business cycle shocks, in contrast with their long-run stabilizing effect documented in Blanchard and Katz (1992). This illustrates the importance of incorporating migrations into regional business cycle models when studying the dynamics of regional prices.

Interaction of income and credit shocks Despite the positive effect of income shocks in low-price MSAs, the reason why house prices still decline in *both* regions in the full experiment, is that the income and credit shocks interact. First, the tightening of mortgage credit in both regions decreases households' incentives to move to affordable regions to buy. Second, θ_{PTI} interacts multiplicatively with individual income Y in determining the maximum affordable price $\overline{P}$, as the formula of Section 2.6 shows:

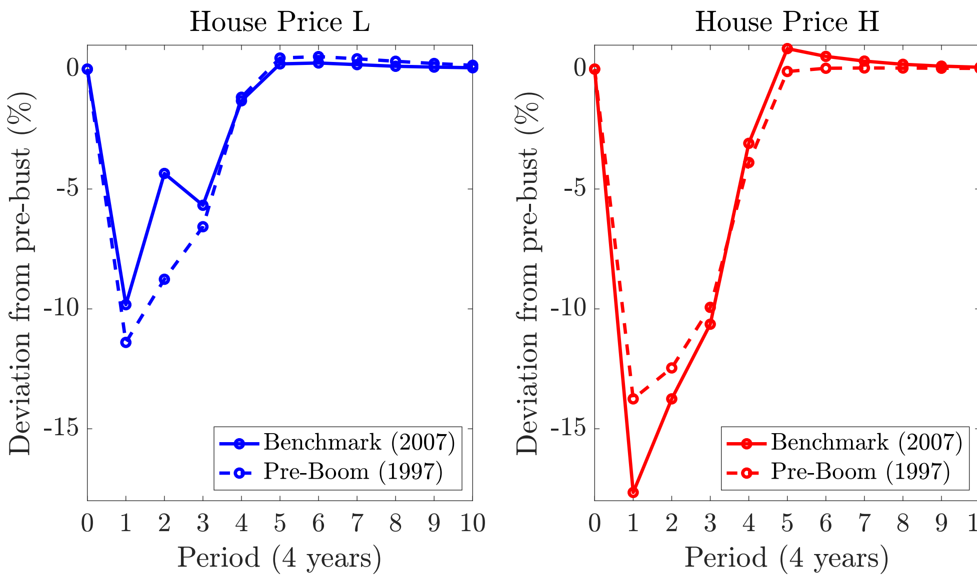
$$\overline{P} = \min\left[\frac{1-(1+r^b)^{-n}}{r^b}\theta_{PTI}Y + \text{down}, \frac{\text{down}}{1-\theta_{LTV}}\right]. \tag{33}$$

5.3 More Unequal Price Distributions Imply More Unequal Responses

To illustrate how house price levels affect young buyers' credit constraints across regions, I run a counterfactual experiment with the less heterogeneous house price distribution of 1997. In 1997, average house prices in Region L were equal to \$95,000 (versus \$120,000 in 2007), and to \$110,000 in region H (versus \$217,000 in 2007).[40] As Figure 9 shows, the effect of regional credit constraints is muted: the less unequal distribution implies less unequal responses ex post, and a smaller aggregate bust. This result is the general equilibrium counterpart of the experiment of Beraja et al. (2019a). It implies that policies which seek to stabilize aggregate prices should focus on high price regions, a result that I explore when studying place-based policies (Section 7.2).

[40] I also calibrate price to rent ratios to their values of 1997, 12.6 in both regions, and credit standards to their pre-boom values. My result that a more unequal price distribution leads to more unequal responses are amplified when keeping credit standards the same as in the main experiment.

Figure 9: Response of house prices to an aggregate recession under the 1997 and the 2007 regional distributions of house prices



Data source: Zillow. Changes in percentage terms relative to the pre-bust period (2006).

6 Long- and Short-Run Dispersion in Housing Markets

This section studies the determinants of the transmission channel of the previous section: first, the primitive parameters governing regional heterogeneity in the model; second, the worse initial conditions of young buyers during the 2010s.

6.1 Drivers of House Price Differences: Housing Demand vs. Supply

First, I study how the regional parameters estimated in the calibration section affect the equilibrium of housing markets. Table 8 shows the steady state housing quantities and prices when shutting down the sources of regional heterogeneity one at a time. Higher amenities $\chi_H > \chi_L$ are responsible for house prices being on average \$72,647 higher in Region H than in Region L, and therefore for local home ownership and young home ownership being respectively lower by 5 pp and 16 pp.[41] Because young households who cannot afford high-price MSAs buy in low-price MSAs, the local young home ownership rate in those regions is slightly higher (+3 pp), and the price is slightly lower (-\$4,250) because the marginal home buyer is poorer. The role of amenities in driving large re-

[41] Incorporating average productivity differences between MSAs would lower these estimates, but would not change the contribution of demand-side factors to the transmission mechanism (amenities, income).

gional differences in the cost of housing is consistent with many empirical estimates, e.g. recently Diamond (2016) and Epple, Quintero and Sieg (2019).[42]

The effect of supply side factors, the cost of residential investment and the price-elasticity of housing supply, is substantial, but lower. I estimate that differences in the cost of residential investment implied by $\overline{I}_H < \overline{I}_L$ contribute to prices being \$24,110 higher in high price regions, with therefore a slightly depressing effect on the young home ownership rate (-3 pp). This factor captures limits on housing supply which are both physical (like mountains or coasts) and regulatory (such as captured by the Wharton Residential Urban land Regulation Index of Gyourko, Saiz and Summers (2008)). The price-elasticity parameter ρ_j has little effect on the levels of variables in steady state, but it does affect the response of variables to shocks.

Table 8: Transmission channel: long run, remove from bench

Variable	Bench	Same amenities	Same res. inv. cost	Same HSE
P_L (\$k)	120,370	124,620	115,848	121,619
R_L (\$)	999	1,063	888	961
ho_L^{young}	0.57	0.54	0.52	0.55
ho_L^{all}	0.69	0.74	0.66	0.68
P_H (\$k)	217,100	144,453	192,990	215,585
R_H (\$)	1,386	1,622	753	1,068
ho_H^{young}	0.38	0.54	0.41	0.40
ho_H^{all}	0.67	0.72	0.66	0.66

Notes: In the benchmark model, high price regions H have a higher amenity value, more costly residential investment, and a lower price-elasticity of housing supply. The columns after "Bench" display the steady state values of variables when separately setting each of these parameters equal to their values in low price regions L. "Same amenities": $\chi_H = \chi_L$. "Same res. inv.": $\overline{I_H} = \overline{I_L}$. "Same HSE": $\rho_H = \rho_L$.

Figure 31 in Appendix describes the economy's response to the same recession under the different counterfactual scenarios. In the benchmark model, the price drop in high price regions is 8 pp larger than in low price regions. When $\chi_H = \chi_L$, the magnitude and the difference in house price bust are much lower (2.3 pp). Economies where $\overline{I}_H = \overline{I}_L$ and $\rho_H = \rho_L$ have differences of 4.7 and 6.3 pp, closer to the benchmark. The small contribution of differences in supply elasticity to generating cross-section variation in housing busts in this period is consistent with the empirical findings of Davidoff (2013). In

[42]They include many unmodeled factors associated with living in a location, such as school quality, climate, leisure amenities like museums, and so forth. My results complement this literature. First, amenities affect not only the level, but also the dynamics of prices, as in Guerrieri et al. (2013) (because of regional credit constraints rather than neighborhood externalitie). Second, allowing for a home ownership margin allows to separately highlight the effects on rental and owner-occupied markets.

contrast to the literature which emphasizes the role of supply constraints for the long-run dynamics of prices, amenities turn out to be a larger contributor to house price volatility at business cycle frequency.

6.2 Cohort-Specific Characteristics

Next, I study how the characteristics of the cohort of Millennial buyers which entered the housing market during the 2010s affect the long-run equilibrium and the short-run volatility of housing markets.

6.2.1 Worse Initial Conditions

In the benchmark model, households start their life-cycles in the 2010s with (1) lower initial net asset positions, calibrated to match the average student debt burden. (2) They draw their initial income from a distribution which is first-order stochastically dominated by the initial distribution in normal times, and this initial draw has a persistent negative effect on their lifetime income.

Table 9 displays the steady state values of prices and home ownership in counterfactual economies where each of those characteristics is shut down one at a time ("No SD" for student debt, "No GR" for the negative effect of graduating in a recession). The directional effects of those factors are similar. By making both LTV and PTI constraints more likely to bind, they lower house prices and average home ownership in both regions. The effect of student debt on home ownership is significant, consistent with recent empirical estimates (Bleemer et al. (2017)), but the effect of graduating in a recession is larger. This is because it directly makes both constraints more binding.

The effect of worse initial conditions on young home ownership and rents is heterogeneous across regions. They significantly decrease young home ownership in high-prices MSAs (student debt by 8 pp and graduating in a recession by 15 pp), but they slightly increase it in low-price MSAs. This is because high house prices lead a fraction of the marginal buyers in high-price regions to relocate to lower price regions. Absent worse initial conditions, those buyers would have stayed in high price regions and waited enough to accumulate a larger down payment and reach higher income levels. This is consistent with the empirical evidence that Millennials increasingly locate in less expensive areas, such as Denver and Austin (Frey (2019)). The relocation of those households further contribute to lowering prices in high price regions. A fraction of young buyers in high price regions chooses to switch to the local rental market. The effect is to *boost* local rents, by up to \$106 per month (+8.3%) for student debt.

Table 9: Transmission channel: long run, remove from bench

Variable	Bench	No SD	No GR	Free migration	No migration
P_L (\$k)	120,370	122,833	127,932	120,454	140,370
R_L (\$)	999	1,161	1,100	1,506	666
ho_L^{young}	0.57	0.40	0.49	0.50	0.52
ho_L^{all}	0.69	0.69	0.71	0.68	0.70
P_H (\$k)	217,100	222,447	230,276	199,396	170,100
R_H (\$)	1,386	1,280	1,316	1,514	2,165
ho_H^{young}	0.38	0.46	0.53	0.38	0.44
ho_H^{all}	0.67	0.69	0.73	0.62	0.66

Notes: The benchmark model features student debt ("SD") and a persistent negative effect on earnings of graduating in a recession ("GR"). The columns after "Bench" display the steady state values of variables when separately removing various those features from the benchmark model.

6.2.2 Neutral Effect on the Pass-Through of Shocks to Prices

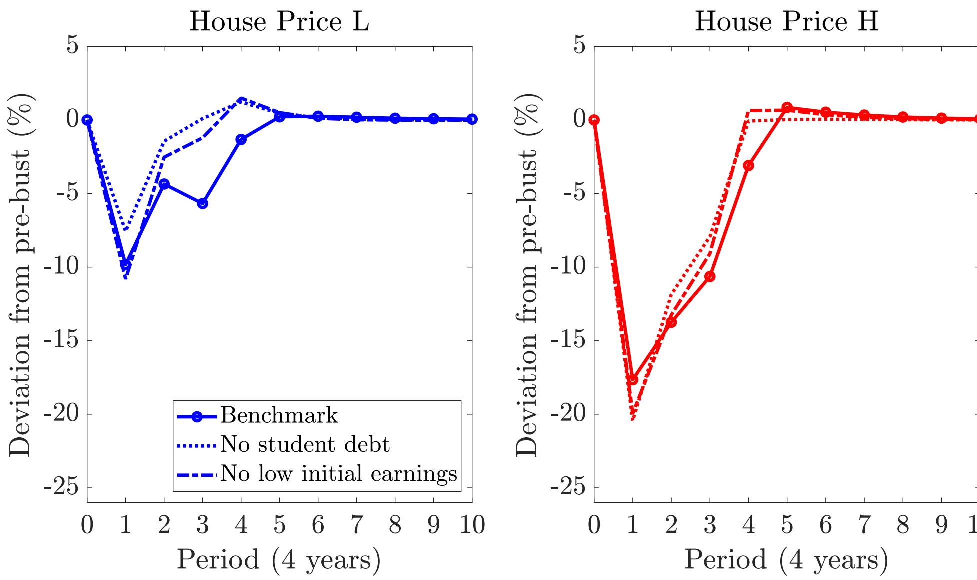
While initial conditions have a significant effect on housing markets in steady state, they do not affect the economy's response to shocks (Figure 10). Two counterbalancing forces are at play. On the one hand, worse initial conditions make buyers' adjustment rates more elastic to shocks, which should amplify price declines. On the other hand, economies without worse initial conditions have lower steady state prices, which makes adjustment rates less elastic to shocks. The net effect on the dynamics of prices is close to zero.

6.2.3 Regional Mobility

The cohort of home buyers during the 2010s also stands out by its low mobility. Regional migration has declined since the 1990s (Kaplan and Schulhofer-Wohl (2017)), young households are more likely to stay or go back live with their parents during recessions (Kaplan (2012)), especially Millennials (Fry (2013)). The "No migration" column of Table 9 shows results for an economy where $m = +\infty$, and the "Free migration" column for $m = 0$. The baseline model lies between the polar cases of models with a single housing market or disconnected housing markets (e.g. Kaplan et al. (forthcoming) or Hurst et al. (2016)), and models with frictionless migrations.

Spatial sorting is a key determinant of housing markets in the long run, such that

Figure 10: Response of house prices to an aggregate recession in the absence of worse initial conditions for the Millennial cohort



Notes: Changes in percentage terms relative to the pre-bust period.

abstracting from it biases inference about regional prices.[43] Absent spatial sorting ("No migration"), steady state prices would be +$20,000 higher in low-price MSAs and -$47,000 lower in high-price MSAs. Without migrations, the composition of the local populations is fixed. The marginal home buyer is richer in low-price MSAs and poorer in high-price MSAs than with spatial sorting, leading respectively to higher and lower prices. As a result, the home ownership rate of the young, whose decision to buy is more price-elastic, is lower by 5 pp in low-price MSAs and higher by 6 pp in high-price MSAs. Since the steady state distribution of house prices is more equal, so are their responses to the credit contraction, at odds with the data (Appendix Figure 32). The opposite happens with with frictionless sorting ("Free migration"). Differences in price responses are exacerbated, and the shocks even lead to an increase in prices in low-price MSAs, also at odds with the data. Thus positive but limited buyers' mobility is key to match steady state prices and their short-run volatility.

[43] Unless the local distributions of age, income, and wealth, are chosen exogenously to match their empirical counterparts and fed to the model. In that case the model would match the pre-bust data in the period when the distributions are taken from. But because of the Lucas critique, comparative statics and transition dynamics exercises would be biased.

7 Regional Heterogeneity and Housing Stimulus Policies

This section evaluates the effect of young buyers' credit constraints on the transmission of stimulus policies in spatial equilibrium. I study existing policies which focus on young buyers, and compute general equilibrium effects which supplement local treatment effects based on empirical estimates.

7.1 The First-Time Home Buyer Credit

7.1.1 Background

I follow Berger et al. (2019), and focus on the second version of the First Time Homebuyer Credit (FTHC) in the 2009 American recovery and Reinvestment Act. The policy is modeled as an $8,000 unanticipated subsidy for households with income below $112,500 which lasts for the length of the housing bust (12 years). [44] I first assume that the policy is not financed when implemented.

7.1.2 Result: Regional Heterogeneity Dampens Aggregate Stimulus

Housing Markets Figure 11 presents the effect of the policy on young home ownership and house prices, across regions and nationwide. These effects quantitatively align with the estimates of Berger et al. (2019). The FTHC subsidy directly makes LTV constraints less likely to bind, and indirectly makes PTI constraints less likely to bind because buyers need to borrow less. It stimulates young home ownership by about 5 pp in low price regions and 10 pp in high price regions, resulting in an increase in home sales of about 10%.[45] It stabilizes the aggregate price index by about 1 pp, an effect coming mostly from dampening the price decline in low-price MSAs.

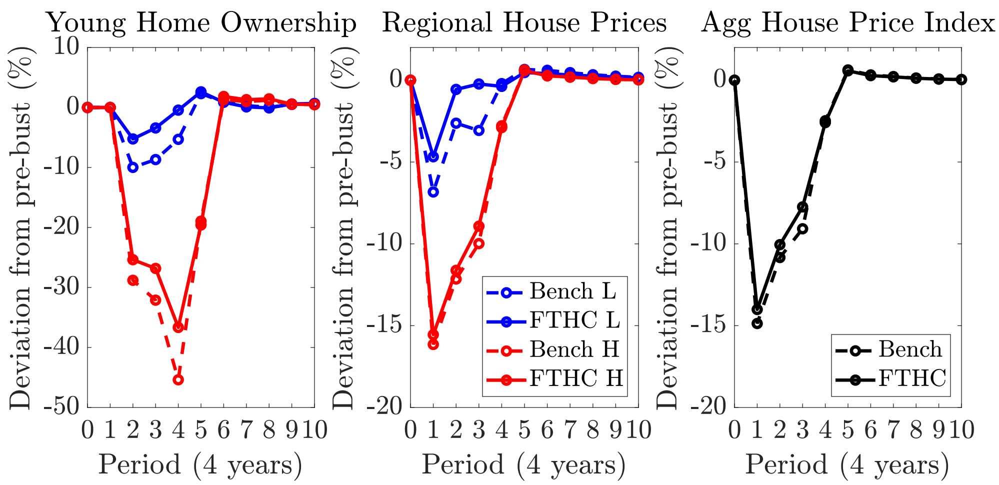
While the policy stimulates young home ownership and prices in low-price MSAs, it fails to stimulate high-price MSAs relatively as much, limiting the aggregate stimulus.[46] This is because the subsidy is a higher fraction of the house price in low-price than in high-price MSAs (6.6% vs. 3.7%), therefore is more likely to induce buyers to purchase houses at higher rates in the former.

[44]The model policy lasts longer than the 2008-10 program.

[45]In the model, the increase in home sales is due to more sales from older to younger households, and more residential investment. In the data, the increase came mostly from a decrease in the stock of existing vacant homes. My model abstracts from vacancies, a usual assumption.

[46]Both value- and population-weighted aggregate house price indices, as well as median transaction-based indices, depend more on house prices in high-price regions, which also have larger populations.

Figure 11: Effect of the First-Time Homebuyer Credit on home ownership and prices

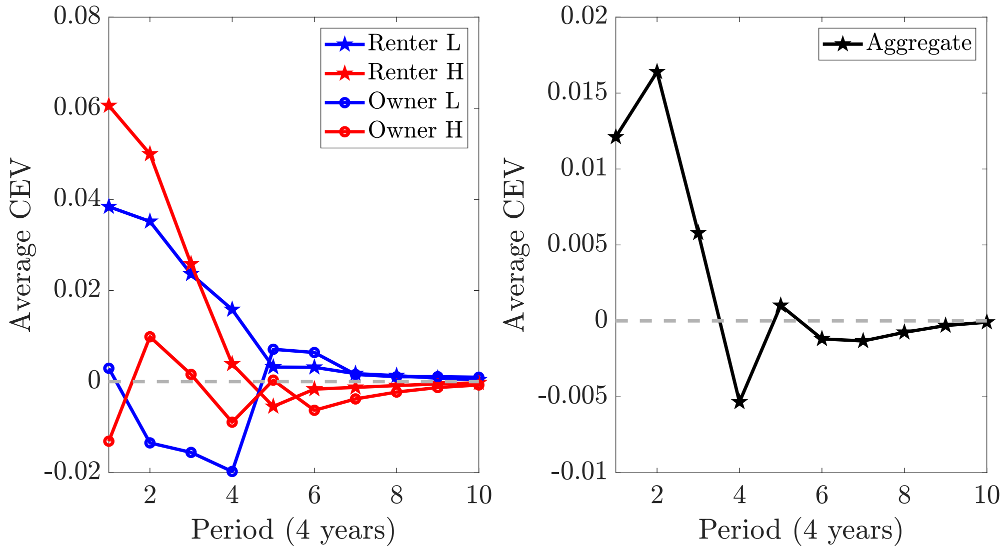


Notes: Left panel: change in young home ownership by region (low price regions in blue, high price regions in red) in the benchmark (dashed line) and with the policy. Middle panel: regional house prices. Left panel: aggregate house price.

Welfare I turn to computing the welfare effects of the policy over the transition. Figure 12 plots consumption-equivalent variations (CEVs), which measure the net welfare gains of the policy in terms of four years (one period) of non-durable consumption. Appendix F details the calculations of CEVs. First, the policy generates a significant welfare gain for the representative (average) household, corresponding to a 1.5% increase in four year consumption. These gains are largest in $t = 2$, when the decrease in house prices is largest, and decrease as households expect to return to pre-bust income and credit standards. They result from both conditional welfare gains for the different categories of households, and changes in the measures of those groups. Second, the policy only benefits renters who buy a house, and has a limited effect on home owners' welfare. Third, the policy benefits renters more in high-price regions (+6% vs. +4% increase in four year consumption), because it allows them to benefit from the larger amenity values and housing quality in those regions ($\chi_H > \chi_L$). Thus even if the policy fails to stabilize home ownership in those regions as much as in low-price regions, the gains for households who access it are larger. The positive effects of the policy on first-time buyers' welfare is persistent, and lasts up to eight years (two period) after the end of the program. Fourth, part of the increase in welfare comes from an increase in the consumption of non-durable goods, which is small but persistent (Appendix Figure 33).

Financing I now consider how stimulus policies are financed by the government. Ricardian equivalence fails with overlapping generations and incomplete markets, so the

Figure 12: Welfare effects of the First-Time Home Buyer Credit over the transition, for different groups and an average household



Notes: Consumption-equivalent variations (CEVs) in terms of four years (one period) of non-durable consumption. For instance, in $t = 1$, the welfare gain of the average renter in high price regions from the policy is equivalent to a 6% increase in its four-year consumption. Conditional average CEVs are computed by aggregating individual CEVs calculated at each point of the state space, using the cross-sectional distribution of households over those states. These responses are for a scenario where the policy is not financed in the foreseeable horizon of existing households.

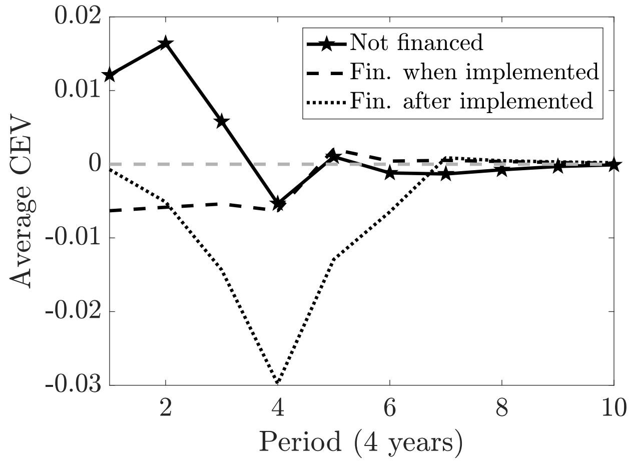
timing of taxes matters for households. The previous results assumed that the policy was not financed in the foreseeable horizon of current households. Figure 13 plots aggregate net welfare gains under this scenario, and compares them to two alternative scenarios: either FTHC is financed at the time of its implementation ($t = 1, 2, 3$), or just after ($t = 4, 5, 6$). In both cases, the same dollar value of FTHC is financed with an increase in distortionary taxes. The tax increase is engineered by decreasing φ from φ_{bench} to φ_{FTHC} in the tax schedule, such that the increase in total net taxes collected equals the value of the FTCH:[47]

$$\int \left(y - \varphi_{FTHC} y^{1-\tau} \right) d\lambda_{FTHC}(y) - \int \left(y - \varphi_{bench} y^{1-\tau} \right) d\lambda_{bench}(y) = FTHC \tag{34}$$

When financed over the lifetime of households who benefit from the FTHC, the policy becomes welfare-reducing. It generates net welfare losses, which are persistent because distortionary taxes slow down wealth accumulation, hence future consumption. This finding is true for any timing of taxes, and is another reason why the stimulus effect of FTHC is limited. Appendix Figure 34 decomposes these results across tenure groups.

[47]Note that the cross-sectional distribution of households λ is different in the two economies.

Figure 13: Welfare effects of the First-Time Home Buyer Credit over the transition, under different tax financing scenarios



Notes: Average consumption equivalent variations (in terms of four years of non-durable consumption) for the average household in the economy. Solid line: FTHC policy not financed. Dashed line: financed at the time it is implemented. Dotted line: financed one period (four years) after it is implemented.

7.2 Place-Based Housing Subsidies

The fact that regional heterogenenity dampens the transmission of stimulus policies to aggregates suggest that it may be more efficient to give different tax credits to regions, depending on their price levels, rather than implementing the policy uniformly.[48] Appendix Figure 35 studies such a policy, where first-time buyers in high-price MSAs receive \$12,000, versus \$4,000 in low-price MSAs. The total dollar cost of the policy is the same as in the previous section. By leaving owners' welfare unchanged, only slightly decreasing renters' welfare in low-price regions, and significantly increasing renters' welfare in high-price regions, this policy manages to increase aggregate welfare by an extra amount equivalent to 1.5% of four-year consumption.

7.3 Credit Relaxation Policy

Credit relaxation policies have long been advocated to counteract the decrease in home ownership (e.g. Goodman (2017)). Here, I study the effect of a 5 pp relaxation of PTI constraints, a policy implemented during the summer 2017 by Fannie Mae.[49] I model it as an unanticipated increase in PTI requirements θ_{PTI} from 45% to 50% in the 2016-19

[48] There are several first-time home buyer programs in the data, to which various lenders participate. They usually offer lower interest rates and down payment requirements, and sometimes subsidies. See for instance the "Achieving the Dream" program in the New York state.

[49] See e.e. "DTI has risen for conventional conforming loans", *CoreLogic Insight Blog*, March 20, 2019.

period just after the bust.

Appendix Figure 38 shows the paths of CEVs for this policy. Unlike the FTHC, the policy significantly stimulates young home ownership in high price regions (+3 pp vs. +1 pp in low price regions). Instead of giving households in each region the same dollar amount to buy houses with different prices $P_H > P_L$, it directly relaxes local borrowing constraints. This policy is a Pareto improvement, with welfare improving for all households. It has persistent positive effects on welfare, expected to last up to the early 2020s, six periods (24 years) after the beginning of the bust. In general equilibrium, the stabilizing effect on prices is however limited (Appendix Figure 36), a sign that stable housing prices are not necessarily a good statistics for households' welfare. Finally, the policy slightly increases consumption because it allows buyers to borrow more.

7.4 Robustness: Local Shocks and Mortgage Default

Many existing policies, such as the Home Affordable Modification Program, consider mortgage delinquencies and foreclosures as the main source of housing market volatility. I conclude by showing that my results on FTHC policies are robust to allowing for default.[50]

For this exercise, I extend the model along three dimensions. First, I allow for heterogeneous exposures of local income processes to aggregateincome, $\beta_H > 1 > \beta_L > 0$. This assumption accounts e.g. the feedback from house prices into local income (Mian and Sufi (2014)). Second, I assume that during the recession, households' valuations of owner-occupied units fall (they are modeled as a component χ_j^O of amenities χ_j in regions j). This is analogous to the belief shocks commonly used in the housing literature (e.g. Kaplan et al. (forthcoming)). Third, I allow households to default on mortgage debt. The "double trigger" motive for default (e.g. Campbell and Cocco (2015)) is the only reason why households default in the model. It allows underwater borrowers in need of liquidity, for instance after a negative income shock, to smooth consumption.

Section H in Appendix shows the fit of the model and policy results. The default cost d is calibrated to match the average frequency of default prior to the bust (2005), measured as the economywide foreclosure rate of 0.2% in RealtyTrac data. It generates a life-cycle profile of default rates similar to the data, with the young defaulting more (Piskorski

[50] I will also study whether my results on credit relaxation policies extend. A limitation of these policies is that they may increase default by risky borrowers and hurt lenders. A complete welfare evaluation would require to model the mortgage sector too.

and Seru (2018)). Exposures β_j are estimated in the data (see calibration section), and the decrease in households' valuations $\left\{\chi^O_{j,t}\right\}$ are chosen to match the residual decrease in house prices (as in Guren and McQuade (forthcoming)), so that the model replicates the entire decrease in regional prices during the bust. Appendix Figure 39 decomposes the contributions of income and credit shocks in the benchmark model, and in the cases with heterogeneous exposures and valuation shocks. During the transition, default rates initially increase as a result of lower prices and income shocks. This is the direct result of the shocks and the indirect result of amplification: defaults increase the supply of homes on the market, which further triggers price decreases, which induce more defaults, and so forth. However, the default rates rapidly fall as a result of the tightening of credit standards, which lowers the probability that new buyers default on their mortgages, all else equal.

When the FTHC is implemented, the welfare of the representative agent in the economy still increases, despite rising default rates due to more risky borrowers accessing home ownership. Due to the absence of lenders in the model, these results are an upper bound on the welfare effects of the FTHC with default. A complete welfare evaluation with a mortgage sector, lenders' welfare losses, and a potential feedback into borrowers' spreads, is left for an extension.

8 Conclusion

The decline in young home ownership, which dramatically accelerated after 2007, is one of the main features of housing markets in the post-Great Recession era. This paper shows that to understand its effects on home buyers and prices, it is critical to account for *spatial* heterogeneity across housing markets. The larger effect of housing busts on young buyers is a channel which explains the regional dispersion in home ownership and price declines when credit contracts. Because young buyers are more constrained in regions with higher prices, they disproportionately respond to changes in credit standards, resulting in larger busts, even where local supply is unconstrained. Regional house price differences dampen the effect of subsidies to young buyers, weakening aggregate stimulus and welfare gains. In contrast, a relaxation of payment-to-income requirements for new buyers, a policy recently implemented at a small scale, achieves larger gains. It uniformly relaxes credit constraints across regions, and thus its effectiveness is independent of the level of local prices.

The spatial framework which I have developed, where the evolution of the regional distribution of house prices is endogenous, allows for many extensions. In particular, I plan to use it to quantify the feedback between house prices and local labor markets, and to jointly explain the higher volatility of expensive regions and of cheaper houses. While centered on housing markets, my analysis extends to the study of how other local prices respond to local, national, and international shocks, as well as to place-based and national policies. Studying their effects in a spatial framework which incorporates risk and risk aversion is important for modern economies where households are mobile and make rich portfolio choices. Beyond real estate, these questions have applications in macroeconomics, finance, and trade.

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Appendix

A Data Appendix

A.1 Dataset Construction

To construct the regional panel dataset used in this paper, I merge public-use data from the U.S. Census Bureau (American Community Survey, County Business Pattern, Building Permit Survey), Zillow, the Consumer Credit Panel of the Federal Reserve Bank of New York, the Home Mortgage Disclosure Act, Fannie Mae and Freddie Mac, and proprietary data from RealtyTrac (purchased through ATTOM Data Solutions).

First, I extract the Census data through American FactFinder. I use ACS variables for which there is information for various age groups, and at the MSA level (Geographies: Metro Micro statistical areas: all MSA within US.) Variables are at the household level unless otherwise specified. When available, I use the ACS 5-year estimates.For each year, I used the following tables.

- Age group shares and total population. Topics: people: age and sex: age. Table: age and sex, ACS 5 year estimates.

- Homeownership rate by age. Topics: housing: occupancy characteristics: owner/renter (tenure in occupied units). Topics: housing: occupancy characteristics: age of householder. Table: tenure by age of householder.

- Income by age. Topics: people: age and sex: age of householder. Topics: people: income and earnings: income/earnings (households). Table: median household income in the past 12 months (in adjusted dollars for the corresponding year) by age of householder, ACS 5 year estimates. This is median income; it includes all sources of income; I construct labor earnings by MSA from the CBP data.

- Employment status by age. Topics: people: employment: employment (labor force) status. Table: employment status, ACS 5 year estimates.

- Aggregate house value by age. Topics: people: age and sex: age of householder. Table: aggregate value (dollars) by age of householder, ACS 5 year estimates.

- Construction: number of establishments, number of paid employees, first quarter payroll (in thousand dollars of the corresponding year), annual payroll (in thousand dollars). Industry codes: "construction": NAICS based industry: 23 construction. Table: geography area series: county business pattern (business pattern for the corresponding year). Available for all NAICS sub-categories.

Second, I complement the construction data from the CBP with data from the Building Permits Survey, directly downloaded from the Census website. It has information, by MSA and year, on the number and dollar amount of permits issued for various building sizes (structures with 1, 2, 3-4, and 5+ units). I use data from the 2014 and 2004 universes (the 2014 universe includes approximately 20,100 permit-issuing places and is used from January 2014 forward; the 2004 universe includes approximately 19,300 permit-issuing places and is used from January 2004 to December 2014.)

Third, I obtain data on median home prices and rents from Zillow's Home Value Index (ZHVI) and Rental Index (ZRI), which are seasonally-adjusted ideal price indices based on a machine-learning algorithm that uses the sale prices of a set of homes with a constant composition over time. I use Zillow's crosswalk between its regions and federally defined MSAs to obtain the data at the MSA level. The frequency is monthly. I annualize the data by calculating an unweighted average across months for each MSA.

Fourth, I obtain data on mortgage credit from HMDAn and Fannie Mae and Freddie Mac through Recursion Co, a financial analytics firm which has aggregated the data at the MSA level for research purposes. It includes information on the number of applications and of loans originated, their dollar values, application statuses, and the characteristics of originated loans. Application statuses are: whether the loan was originated, the application was approved but not accepted, denied by the financial institution, withdrawn by the applicant, the file closed for incompleteness, the loan purchased by the institution, the preapproval request denied by the financial institution, or the preapproval request approved but not accepted (optional reporting).

Fifth, I use the data on housing supply elasticity by MSA made publicly available by Albert Saiz.

Sixth, I use data on the number and balances of mortgages originated to first-time buyers, broken down by 10-year age bins and aggregated at the MSA level, from the New York Fed's CCP.

Then, I create a script to process the CSV and Excel tables for each of those variables for each year, and aggregate them across years. I thus obtain one table for each variable, which includes all years and MSAs. When the data is in long format, I reshape it to wide format to keep an (MSA,year) pair as the unique identifier for an observation. For the building permits data, some observations are on several consecutive rows in the Excel file because they are long, in this case I merge those rows into a single row corresponding to an observation.

Because of its specificity, the building permits data has a different treatment detailed in this paragraph. It is in text format, and before 2009 it does not have MSA codes, but it has MSA names, so I merge it with the post-2009 data that has both MSA names and codes, using the following text analysis algorithm. Using text recognition for ",", I split the MSA name between the metro area and the state names (e.g. for "New Orleans, LA", the state is "LA"). I do the same for the metro name itself when it combines several zones using hyphens. For instance, "Albany-Schenectady-Troy" produces three variables: MSA name 1, name 2 and name 3, with respective values "Albany", "Schenectady", and "Troy". All those names are inputs for the text recognition algorithm. Its goal is to fill in the missing MSA codes in the old universe data with help of the new universe data[51]. The steps are as follows. Step 1: look for rows with missing code in the entire table; when a missing value is found, identify the corresponding original MSA name and state, and look in the entire table if there is another row with a non-missing MSA code and the same name and state; if yes, stop, and declare a perfect match, and replace the missing value by the MSA code found; otherwise, do the same without the restriction that the states must be identical, and if a non-missing value is found, stop and declare a match based on CBSA name only; otherwise, go to step 2. Step 2: for unmatched MSA names, use a fuzzy string matching algorithm (based on the Levenshtein distance) to find matching original MSA names, either perfect or approximate. Replace missing values by the found MSA codes, and otherwise go to step 3. Step 3: re-do step 2, now using MSA name 1 (this helps with unmatched hyphenated CBSA names). If there are still unmatched values (this is not the case), then do it for name 2, etc. Finally, delete the unmatched observations (an alternative would be to exploit information based on the observations' values, but at the cost of increased computational complexity).

Then, I merge all those tables using an (MSA code,year) pair as a unique identifier.

Finally, I deflate all nominal variables using the chained CPI for all urban consumers (all items in US city average) from the BLS, equal to 100 in 1999.

Additionally, I perform various checks on the resulting dataset to ensure its consistency. For instance, check that the number of MSAs is between 384 (number of MSAs in the U.S. as defined by the Office of Management and Budget) and 392 (including Puerto

[51] One limitation is if MSA delineations have substantially changed between the old and new universes.

Rico).

A.2 Additional data sources

These data sources supplement those described in the main text, and are used either in the calibration of the model or for control variables in the regressions presented below.

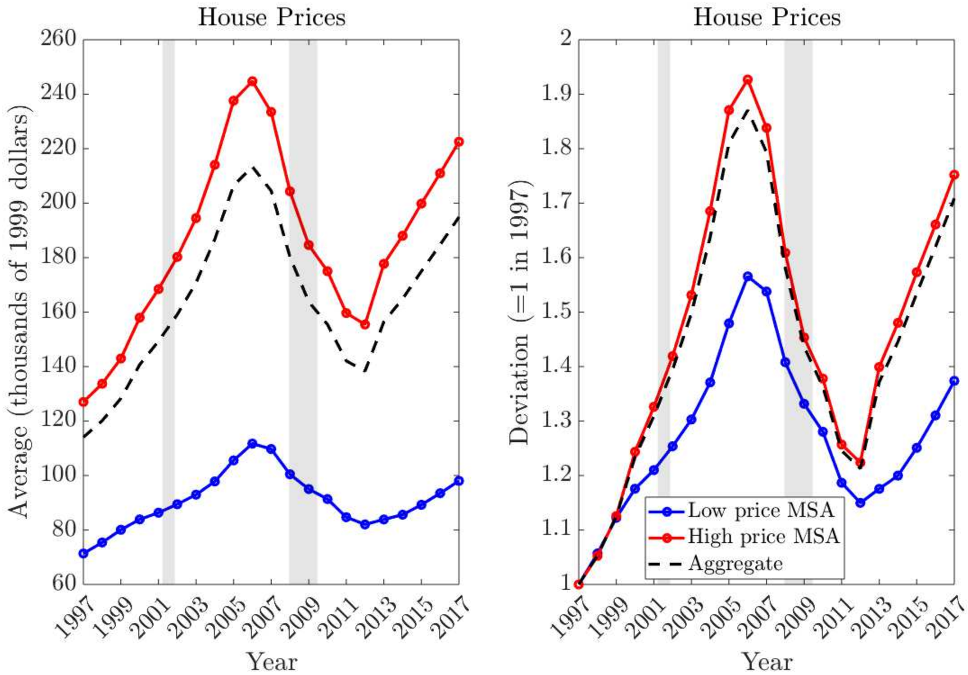
To account for exit from homeownership through foreclosures, I use MSA-level proprietary foreclosure data from RealtyTrac./ATTOM Data Solution. A foreclosure is defined as the union of the following events: notice of default, pending lawsuit, notice of trustee's sale, notice of foreclosure sale, Real Estate Owned property.

To account for housing supply side factors, I collect data from the Building Permits Survey and from the County Business Patterns to proxy for residential investment and construction. It comprises the number and value of all building permits and broken down by type of structures (from 1 to 5+ units), as well as the total number of employees, payroll, and number of establishments in the construction sector (NAICS code 23 and subcodes). I also use MSA-level data on housing supply elasticity as estimated by Saiz, which are do not vary by year.

Finally, to check that my findings are not affected by differences in housing types by region and age, I use detailed panel data from the American Housing Survey (AHS), which I aggregate at the MSA level. In particular, it includes the type of housing unit (e.g. detached single-family home), the number of bedrooms, construction year, and location within or outside an MSA and/or urban and rural areas.

A.3 Sorting Regions by House Price Levels

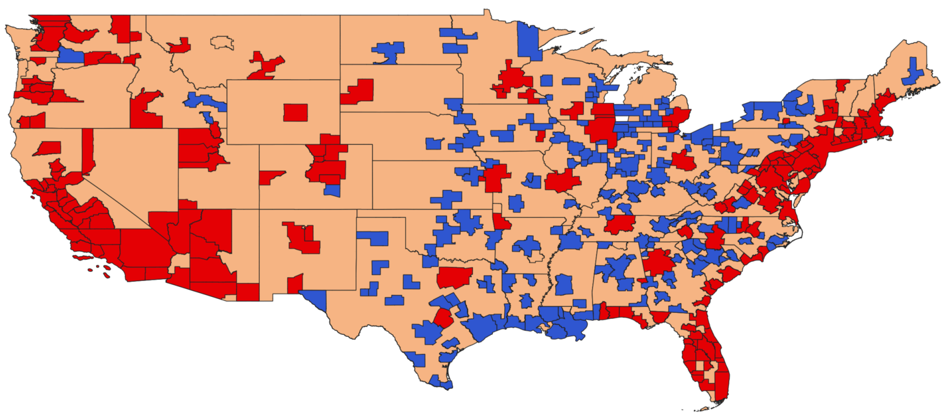
Figure 14: House Prices by Group of MSAs, 1997-2017



Notes: Levels, 1999 dollars (left panel) and deviation from 1997 value, normalized to 1 (right panel). MSAs are sorted into two groups by the level of house prices in 2006 (bottom 50%, blue, and top 50%, red). Within each group, the weighted average rate of a given age group is calculated using the MSA total population in 2007. The shaded area indicates the NBER recessions. Data source: Zillow, ACS.

Robustness I verified that this sorting of MSAs is robust to using alternative house price indices. In particular, Zillow's ZHVI aligns with alternative house price measures like the All-Transaction House Price Index from the U.S. Federal Housing Finance Agency (FHFA) and the S&P/Case-Shiller Home Price Index. For most MSAs my measure of the recovery speed aligns with a measure of the magnitude of the bust (house price deviation from 2007 peak to trough). For instance, Yuma, AZ had both a large bust and a slow recovery. A small fraction of MSAs had a relatively mild bust but a slow recovery, for instance Ann Harbor, MI.

Figure 15: Regional distribution of house price levels



Notes: This map plots the distribution of MSAs grouped by house price levels in 2006 (bottom 50%, blue, and top 50%, red). Source: Zillow.

Table 10: Metropolitan Statistical Areas in the bottom 50% of the house price distribution in 2006

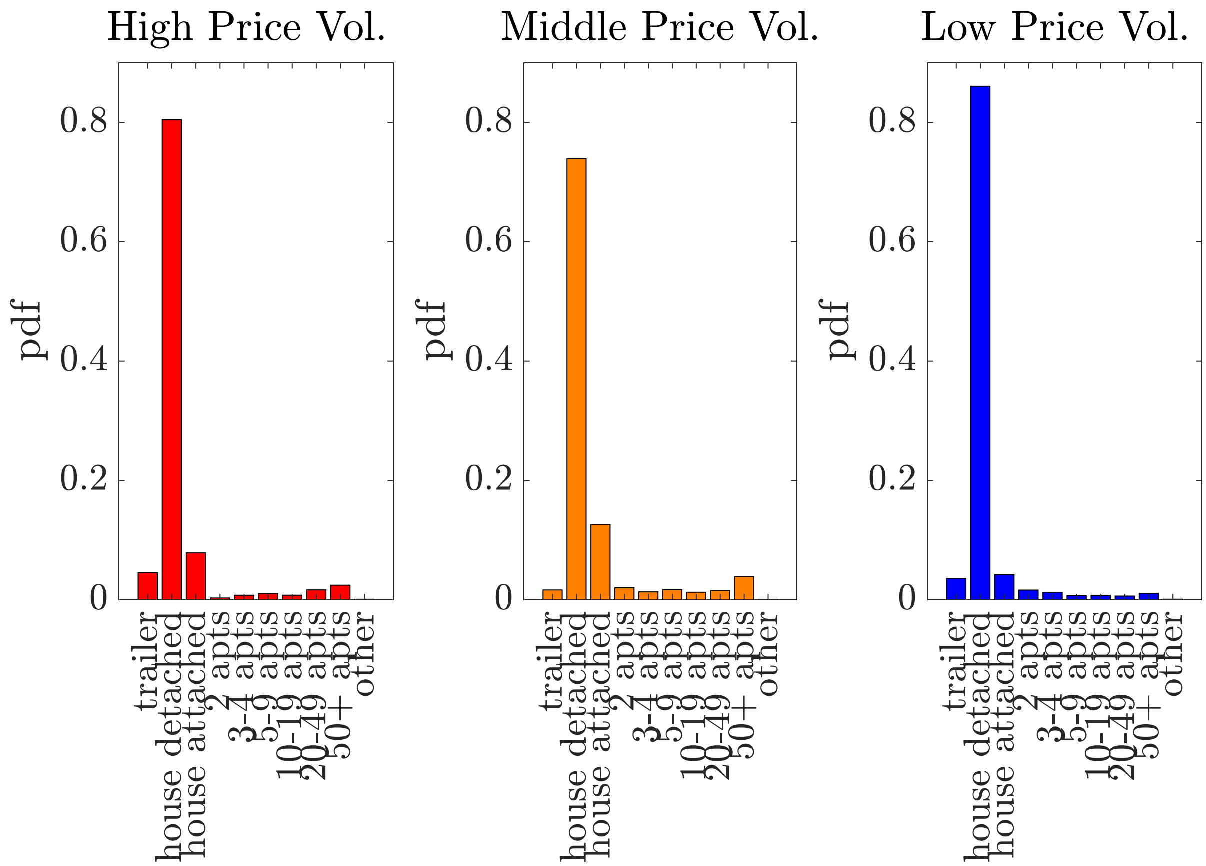
Bottom 50%
Abilene, TX ; Akron, OH ; Albany, GA ; Alexandria, LA ; Altoona, PA ; Amarillo, TX ; Ames, IA ; Appleton, WI ; Athens-Clarke County, GA ; Augusta-Richmond County, GA-SC ; Bangor, ME ; Baton Rouge, LA ; Battle Creek, MI ; Bay City, MI ; Beaumont-Port Arthur, TX ; Beckley, WV ; Binghamton, NY ; Birmingham-Hoover, AL ; Bismarck, ND ; Bloomington, IL ; Bloomington, IN ; Bloomsburg-Berwick, PA ; Bowling Green, KY ; Brownsville-Harlingen, TX ; Buffalo-Cheektowaga-Niagara Falls, NY ; Buffalo-Niagara Falls, NY ; Burlington, NC ; Canton-Massillon, OH ; Cape Girardeau, MO-IL ; Cape Girardeau-Jackson, MO-IL ; Cedar Rapids, IA ; Champaign-Urbana, IL ; Charleston, WV ; Chattanooga, TN-GA ; Cincinnati, OH-KY-IN ; Cincinnati-Middletown, OH-KY-IN ; Clarksville, TN-KY ; Cleveland, TN ; Cleveland-Elyria, OH ; Cleveland-Elyria-Mentor, OH ; College Station-Bryan, TX ; Columbia, MO ; Columbia, SC ; Columbus, GA-AL ; Columbus, IN ; Corpus Christi, TX ; Cumberland, MD-WV ; Dalton, GA ; Danville, IL ; Davenport-Moline-Rock Island, IA-IL ; Dayton, OH ; Decatur, IL ; Des Moines, IA ; Des Moines-West Des Moines, IA ; Dothan, AL ; Dubuque, IA ; Duluth, MN-WI ; Eau Claire, WI ; El Paso, TX ; Elizabethtown, KY ; Elizabethtown-Fort Knox, KY ; Elkhart-Goshen, IN ; Elmira, NY ; Enid, OK ; Erie, PA ; Evansville, IN-KY ; Fargo, ND-MN ; Fayetteville, NC ; Flint, MI ; Florence, SC ; Florence-Muscle Shoals, AL ; Fond du Lac, WI ; Fort Smith, AR-OK ; Fort Wayne, IN ; Gadsden, AL ; Goldsboro, NC ; Grand Forks, ND-MN ; Grand Island, NE ; Grand Rapids-Wyoming, MI ; Green Bay, WI ; Greensboro-High Point, NC ; Greenville, SC ; Greenville-Anderson-Mauldin, SC ; Greenville-Mauldin-Easley, SC ; Gulfport-Biloxi, MS ; Gulfport-Biloxi-Pascagoula, MS ; Hammond, LA ; Hattiesburg, MS ; Hickory-Lenoir-Morganton, NC ; Hot Springs, AR ; Houma-Bayou Cane-Thibodaux, LA ; Houma-Thibodaux, LA ; Houston-Sugar Land-Baytown, TX ; Houston-The Woodlands-Sugar Land, TX ; Huntington-Ashland, WV-KY-OH ; Idaho Falls, ID ; Indianapolis, IN ; Indianapolis-Carmel, IN ; Indianapolis-Carmel-Anderson, IN ; Jackson, MI ; Jackson, MS ; Jackson, TN ; Jacksonville, NC ; Jefferson City, MO ; Johnson City, TN ; Johnstown, PA ; Jonesboro, AR ; Kalamazoo-Portage, MI ; Kankakee, IL ; Kankakee-Bradley, IL ; Killeen-Temple, TX ; Killeen-Temple-Fort Hood, TX ; Kingsport-Bristol-Bristol, TN-VA ; Knoxville, TN ; Kokomo, IN ; La Crosse, WI-MN ; La Crosse-Onalaska, WI-MN ; Lafayette, LA ; Lafayette-West Lafayette, IN ; Lake Charles, LA ; Lansing-East Lansing, MI ; Laredo, TX ; Lawton, OK ; Lexington-Fayette, KY ; Lima, OH ; Lincoln, NE ; Little Rock-North Little Rock, AR ; Little Rock-North Little Rock-Conway, AR ; Longview, TX ; Louisville, KY-IN ; Louisville-Jefferson County, KY-IN ; Louisville/Jefferson County, KY-IN ; Lubbock, TX ; Lynchburg, VA ; Macon, GA ; Macon-Bibb County, GA ; Manhattan, KS ; Mansfield, OH ; McAllen-Edinburg-Mission, TX ; Memphis, TN-MS-AR ; Michigan City-La Porte, IN ; Midland, MI ; Midland, TX ; Mobile, AL ; Monroe, LA ; Montgomery, AL ; Morgantown, WV ; Morristown, TN ; Muncie, IN ; Muskegon, MI ; Muskegon-Norton Shores, MI ; New Bern, NC ; New Orleans-Metairie, LA ; New Orleans-Metairie-Kenner, LA ; Niles-Benton Harbor, MI ; Odessa, TX ; Oklahoma City, OK ; Omaha-Council Bluffs, NE-IA ; Oshkosh-Neenah, WI ; Owensboro, KY ; Parkersburg-Marietta-Vienna, WV-OH ; Parkersburg-Vienna, WV ; Peoria, IL ; Pittsburgh, PA ; Pocatello, ID ; Pueblo, CO ; Rochester, NY ; Rockford, IL ; Rome, GA ; Saginaw, MI ; Saginaw-Saginaw Township North, MI ; San Angelo, TX ; San Antonio, TX ; San Antonio-New Braunfels, TX ; Sandusky, OH ; Scranton–Wilkes-Barre, PA ; Scranton–Wilkes-Barre–Hazleton, PA ; Shreveport-Bossier City, LA ; Sioux City, IA-NE-SD ; Sioux Falls, SD ; South Bend-Mishawaka, IN-MI ; Spartanburg, SC ; Springfield, IL ; Springfield, MO ; Springfield, OH ; St. Joseph, MO-KS ; Sumter, SC ; Syracuse, NY ; Terre Haute, IN ; Texarkana, TX-AR ; Texarkana, TX-Texarkana, AR ; Toledo, OH ; Topeka, KS ; Tulsa, OK ; Tuscaloosa, AL ; Tyler, TX ; Utica-Rome, NY ; Valdosta, GA ; Victoria, TX ; Waco, TX ; Warner Robins, GA ; Waterloo-Cedar Falls, IA ; Watertown-Fort Drum, NY ; Wausau, WI ; Wheeling, WV-OH ; Wichita Falls, TX ; Wichita, KS ; Williamsport, PA ; Winston-Salem, NC ; Yakima, WA ; Youngstown-Warren-Boardman, OH-PA ;

Table 11: Metropolitan Statistical Areas in the top 50% of the house price distribution in 2006

Top 50%
Albany, OR ; Albany-Schenectady-Troy, NY ; Albuquerque, NM ; Allentown-Bethlehem-Easton, PA-NJ ; Anchorage, AK ; Ann Arbor, MI ; Asheville, NC ; Atlanta-Sandy Springs-Marietta, GA ; Atlanta-Sandy Springs-Roswell, GA ; Atlantic City, NJ ; Atlantic City-Hammonton, NJ ; Auburn-Opelika, AL ; Austin-Round Rock, TX ; Austin-Round Rock-San Marcos, TX ; Bakersfield, CA ; Bakersfield-Delano, CA ; Baltimore-Columbia-Towson, MD ; Baltimore-Towson, MD ; Barnstable Town, MA ; Bellingham, WA ; Bend, OR ; Bend-Redmond, OR ; Billings, MT ; Blacksburg-Christiansburg-Radford, VA ; Boise City, ID ; Boise City-Nampa, ID ; Boston-Cambridge-Newton, MA-NH ; Boston-Cambridge-Quincy, MA-NH ; Boulder, CO ; Bremerton-Silverdale, WA ; Bridgeport-Stamford-Norwalk, CT ; Brunswick, GA ; Burlington-South Burlington, VT ; California-Lexington Park, MD ; Cape Coral-Fort Myers, FL ; Carson City, NV ; Casper, WY ; Chambersburg-Waynesboro, PA ; Charleston-North Charleston, SC ; Charleston-North Charleston-Summerville, SC ; Charlotte-Concord-Gastonia, NC-SC ; Charlotte-Gastonia-Concord, NC-SC ; Charlotte-Gastonia-Rock Hill, NC-SC ; Charlottesville, VA ; Cheyenne, WY ; Chicago-Joliet-Naperville, IL-IN-WI ; Chicago-Naperville-Elgin, IL-IN-WI ; Chicago-Naperville-Joliet, IL-IN-WI ; Chico, CA ; Coeur d'Alene, ID ; Colorado Springs, CO ; Columbus, OH ; Corvallis, OR ; Crestview-Fort Walton Beach-Destin, FL ; Dallas-Fort Worth-Arlington, TX ; Daphne-Fairhope-Foley, AL ; Deltona-Daytona Beach-Ormond Beach, FL ; Denver-Aurora, CO ; Denver-Aurora-Broomfield, CO ; Denver-Aurora-Lakewood, CO ; Detroit-Warren-Dearborn, MI ; Detroit-Warren-Livonia, MI ; Durham, NC ; Durham-Chapel Hill, NC ; East Stroudsburg, PA ; El Centro, CA ; Eugene, OR ; Eugene-Springfield, OR ; Fairbanks, AK ; Fayetteville-Springdale-Rogers, AR-MO ; Flagstaff, AZ ; Fort Collins, CO ; Fort Collins-Loveland, CO ; Fresno, CA ; Gainesville, FL ; Gainesville, GA ; Gettysburg, PA ; Glens Falls, NY ; Grand Junction, CO ; Grants Pass, OR ; Greeley, CO ; Hagerstown-Martinsburg, MD-WV ; Hanford-Corcoran, CA ; Harrisburg-Carlisle, PA ; Harrisonburg, VA ; Hartford-West Hartford-East Hartford, CT ; Hilton Head Island-Bluffton-Beaufort, SC ; Homosassa Springs, FL ; Iowa City, IA ; Ithaca, NY ; Jacksonville, FL ; Kahului-Wailuku-Lahaina, HI ; Kansas City, MO-KS ; Kennewick-Pasco-Richland, WA ; Kennewick-Richland, WA ; Kennewick-Richland-Pasco, WA ; Kingston, NY ; Lake Havasu City-Kingman, AZ ; Lakeland, FL ; Lakeland-Winter Haven, FL ; Lancaster, PA ; Las Cruces, NM ; Las Vegas-Henderson-Paradise, NV ; Las Vegas-Paradise, NV ; Lawrence, KS ; Lebanon, PA ; Lewiston, ID-WA ; Lewiston-Auburn, ME ; Logan, UT-ID ; Longview, WA ; Los Angeles-Long Beach-Anaheim, CA ; Madera, CA ; Madera-Chowchilla, CA ; Madison, WI ; Manchester-Nashua, NH ; Mankato-North Mankato, MN ; Medford, OR ; Merced, CA ; Miami-Fort Lauderdale-Miami Beach, FL ; Miami-Fort Lauderdale-Pompano Beach, FL ; Miami-Fort Lauderdale-West Palm Beach, FL ; Milwaukee-Waukesha-West Allis, WI ; Minneapolis-St. Paul-Bloomington, MN-WI ; Missoula, MT ; Modesto, CA ; Monroe, MI ; Mount Vernon-Anacortes, WA ; Myrtle Beach-Conway-North Myrtle Beach, SC ; Myrtle Beach-Conway-North Myrtle Beach, SC-NC ; Myrtle Beach-North Myrtle Beach-Conway, SC ; Napa, CA ; Naples-Immokalee-Marco Island, FL ; Naples-Marco Island, FL ; Nashville-Davidson–Murfreesboro, TN ; Nashville-Davidson–Murfreesboro–Franklin, TN ; New Haven-Milford, CT ; New York-Newark-Jersey City, NY-NJ-PA ; New York-Northern New Jersey-Long Island, NY-NJ-PA ; North Port-Bradenton-Sarasota, FL ; North Port-Sarasota-Bradenton, FL ; Norwich-New London, CT ; Ocala, FL ; Ocean City, NJ ; Ogden-Clearfield, UT ; Olympia, WA ; Olympia-Tumwater, WA ; Orlando-Kissimmee, FL ; Orlando-Kissimmee-Sanford, FL ; Oxnard-Thousand Oaks-Ventura, CA ; Palm Bay-Melbourne-Titusville, FL ; Panama City, FL ; Panama City-Lynn Haven, FL ; Panama City-Lynn Haven-Panama City Beach, FL ; Pensacola-Ferry Pass-Brent, FL ; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD ; Phoenix-Mesa-Glendale, AZ ; Phoenix-Mesa-Scottsdale, AZ ; Pittsfield, MA ; Port St. Lucie, FL ; Port St. Lucie-Fort Pierce, FL ; Portland-South Portland, ME ; Portland-South Portland-Biddeford, ME ; Prescott, AZ ; Providence-New Bedford-Fall River, RI-MA ; Providence-Warwick, RI-MA ; Provo-Orem, UT ; Punta Gorda, FL ; Racine, WI ; Raleigh, NC ; Raleigh-Cary, NC ; Rapid City, SD ; Reading, PA ; Redding, CA ; Reno, NV ; Reno-Sparks, NV ; Richmond, VA ; Riverside-San Bernardino-Ontario, CA ; Roanoke, VA ; Rochester, MN ; Sacramento–Arden-Arcade–Roseville, CA ; Sacramento–Roseville–Arden-Arcade, CA ; Salem, OR ; Salinas, CA ; Salisbury, MD ; Salisbury, MD-DE ; Salt Lake City, UT ; San Diego-Carlsbad, CA ; San Diego-Carlsbad-San Marcos, CA ; San Francisco-Oakland-Fremont, CA ; San Francisco-Oakland-Hayward, CA ; San Jose-Sunnyvale-Santa Clara, CA ; San Luis Obispo-Paso Robles, CA ; San Luis Obispo-Paso Robles-Arroyo Grande, CA ; Santa Cruz-Watsonville, CA ; Santa Fe, NM ; Santa Maria-Santa Barbara, CA ; Santa Rosa, CA ; Santa Rosa-Petaluma, CA ; Savannah, GA ; Seattle-Tacoma-Bellevue, WA ; Sebastian-Vero Beach, FL ; Sebring, FL ; Sierra Vista-Douglas, AZ ; Spokane, WA ; Spokane-Spokane Valley, WA ; Springfield, MA ; St. George, UT ; St. Louis, MO-IL ; Staunton-Waynesboro, VA ; Stockton, CA ; Stockton-Lodi, CA ; Tallahassee, FL ; Tampa-St. Petersburg-Clearwater, FL ; The Villages, FL ; Trenton, NJ ; Trenton-Ewing, NJ ; Tucson, AZ ; Urban Honolulu, HI ; Vallejo-Fairfield, CA ; Vineland-Bridgeton, NJ ; Vineland-Millville-Bridgeton, NJ ; Virginia Beach-Norfolk-Newport News, VA-NC ; Visalia-Porterville, CA ; Walla Walla, WA ; Washington-Arlington-Alexandria, DC-VA-MD-WV ; Wenatchee, WA ; Wenatchee-East Wenatchee, WA ; Wilmington, NC ; Winchester, VA-WV ; Worcester, MA ; Worcester, MA-CT ; York-Hanover, PA ; Yuba City, CA ; Yuma, AZ ;

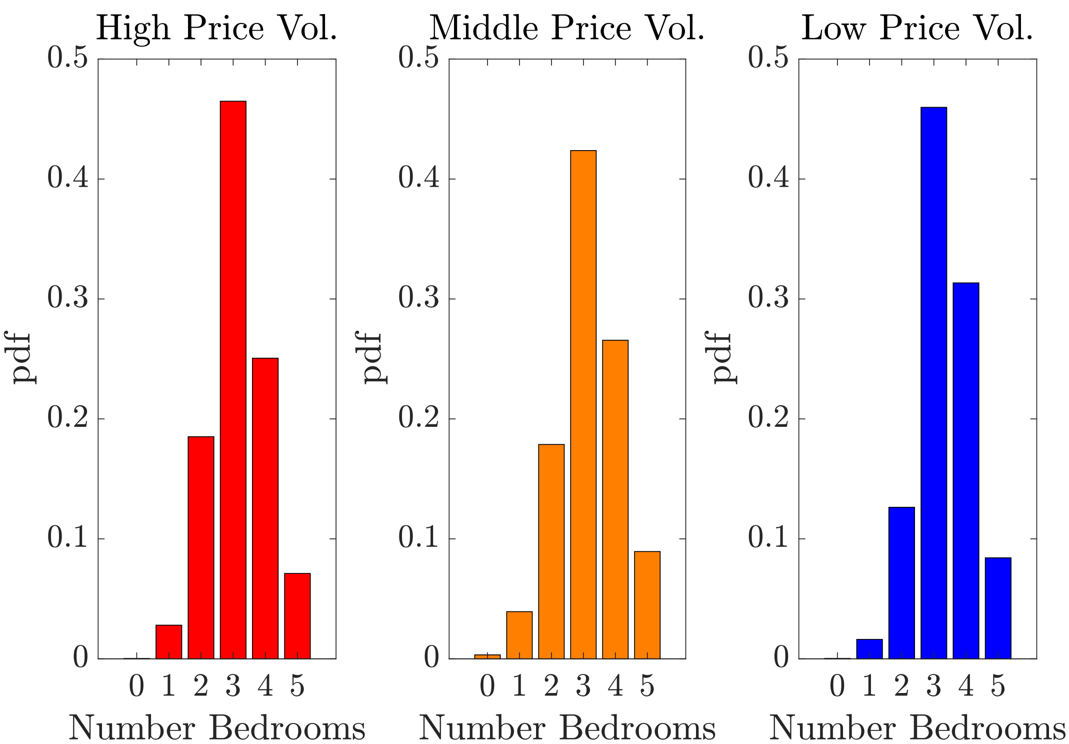
A.4 Housing Characteristics Across U.S. Regions

Figure 16: Regional distribution of housing types: structure



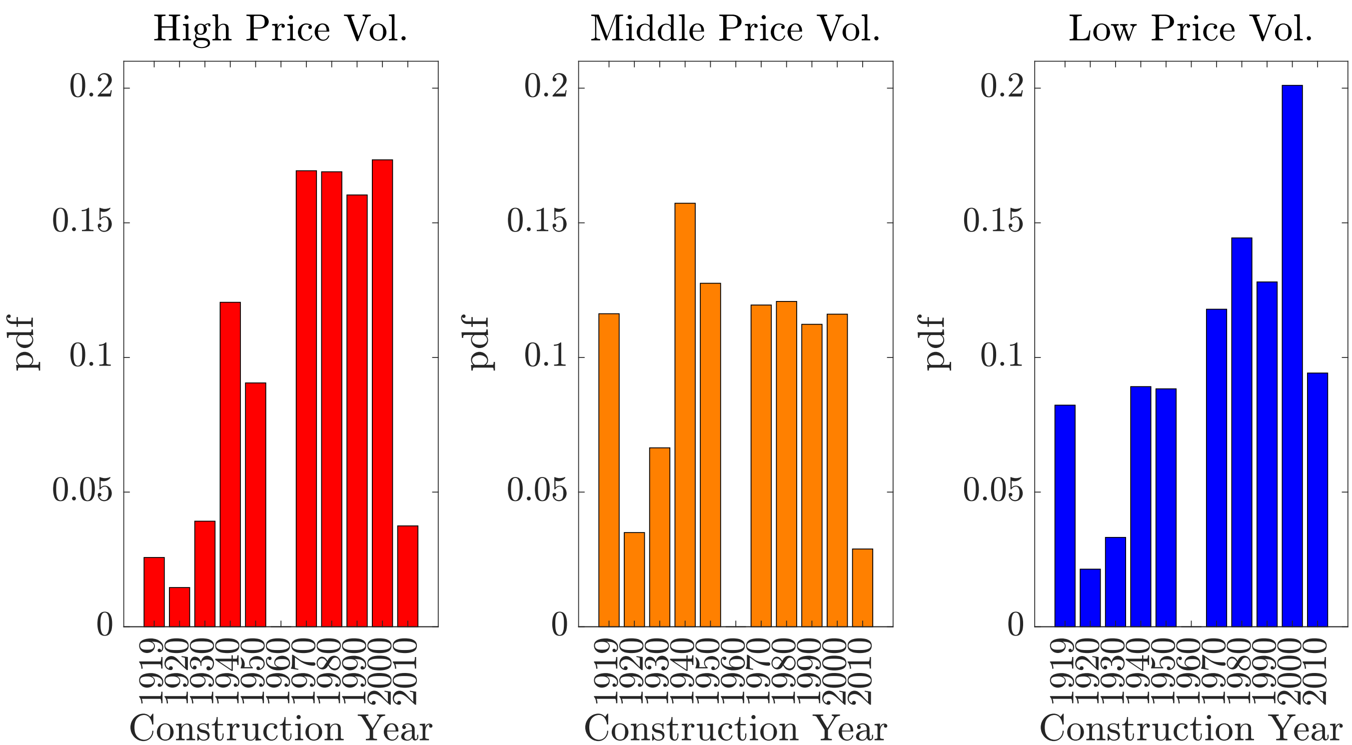
Notes: Data source: Zillow, AHS.

Figure 17: Regional distribution of housing sizes



Notes: Data source: Zillow, AHS.

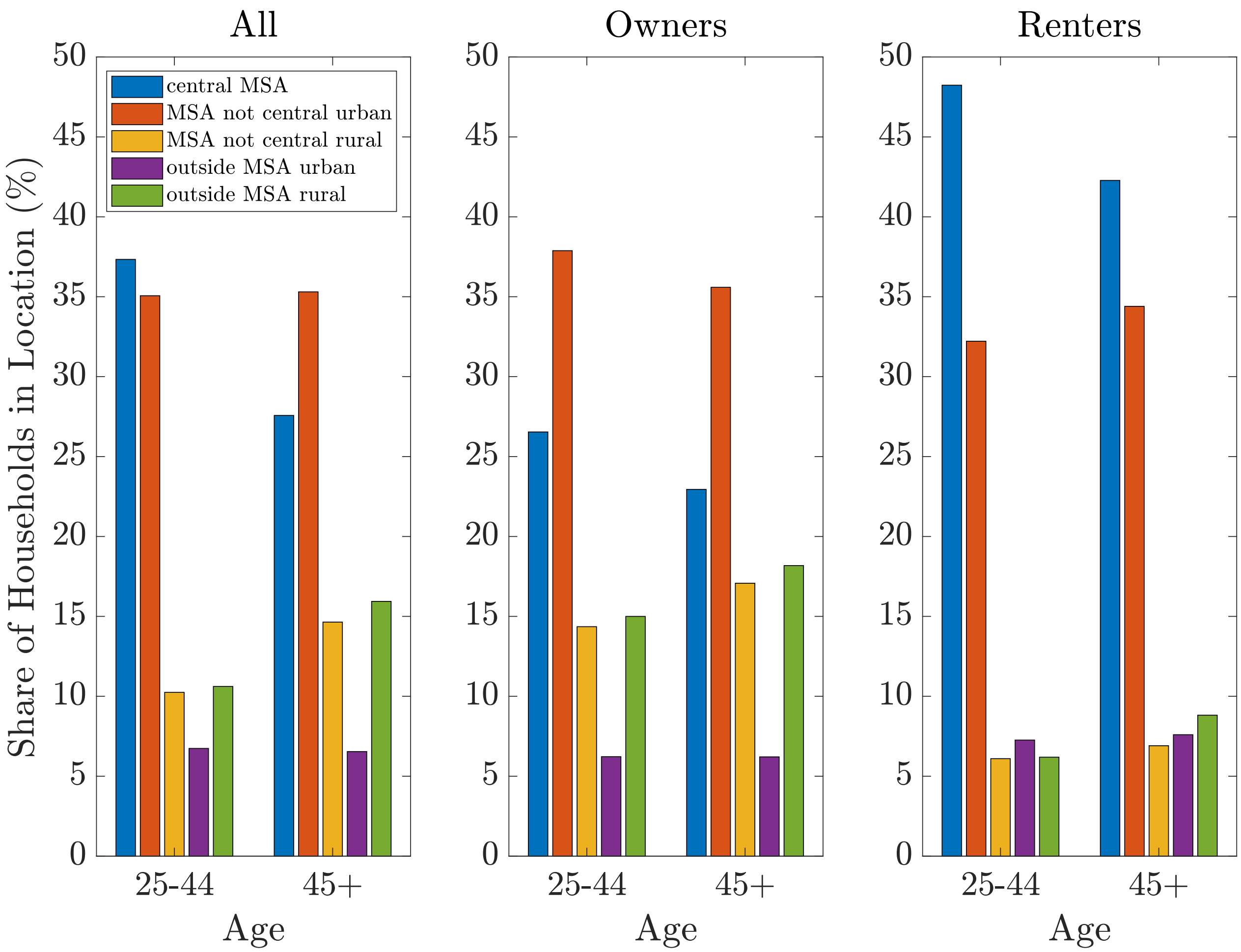
Figure 18: Regional distribution of housing types: building age



Notes: Data source: Zillow, AHS.

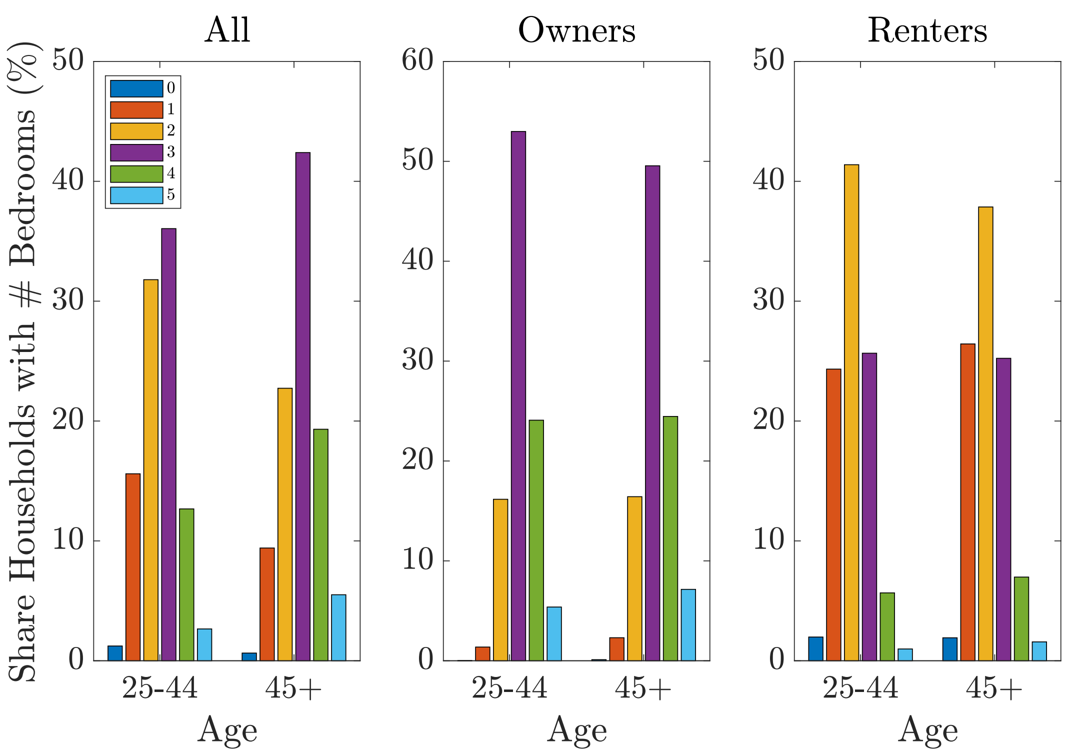
A.5 Housing Characteristics by Age

Figure 19: Distribution of households across region types by age and tenure



Notes: Data source: Zillow, AHS.

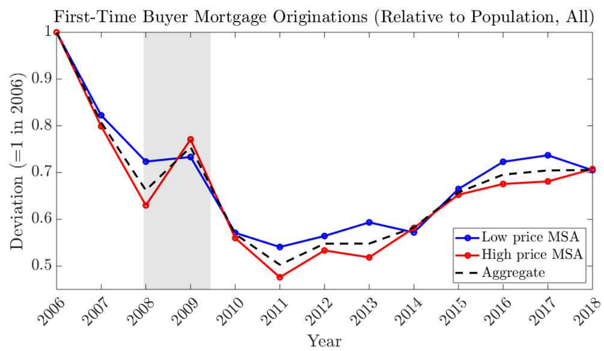
Figure 20: Distribution of households across housing sizes by age and tenure



Notes: Data source: Zillow, AHS.

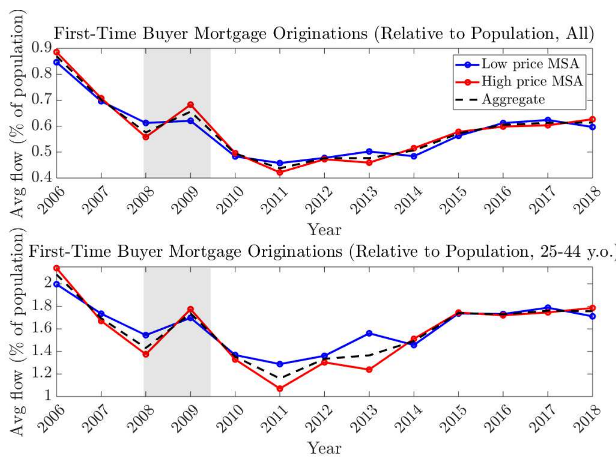
A.6 Robustness: First-Time Mortgage Originations

Figure 21: Flow of first-time mortgages by region: all first-time buyers



Notes: Normalized in 2006

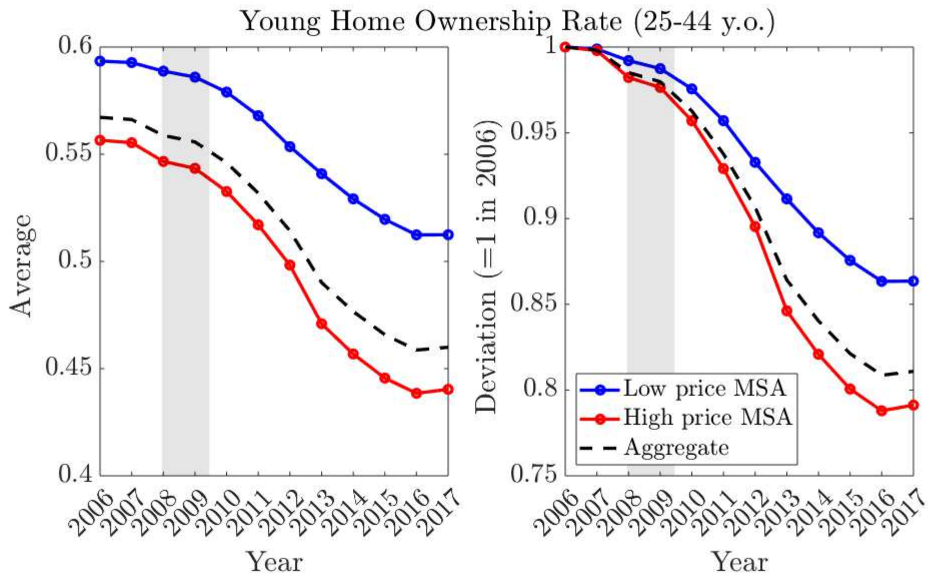
Figure 22: Flow of first-time mortgages by region



Notes: Upper panel: all first-time buyers, flow. Lower panel: young first-time buyers (25-44 y.o.), flow. Relative to population. Population-weighted averages.

A.7 Additional Evidence: Entry and Exit from Home Ownership

Figure 23: Homeownership rates by age across regions

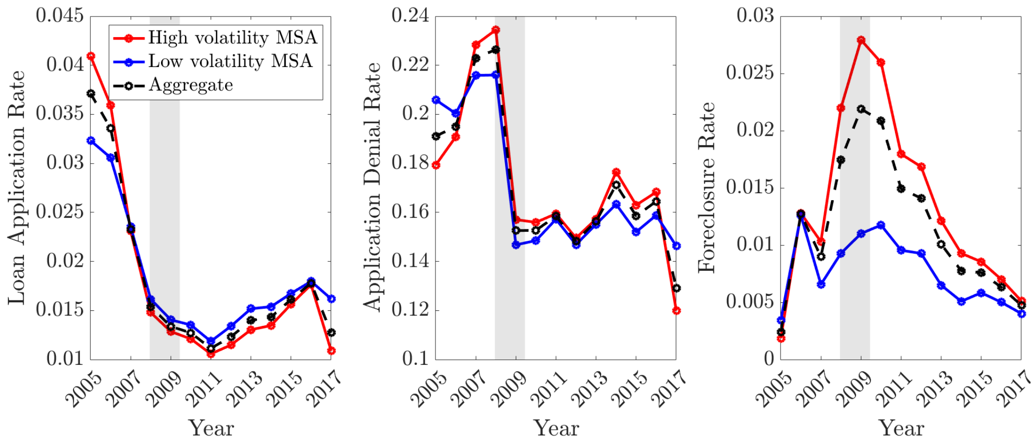


Notes: Left panel: The solid lines depict the average home ownership rate of prime-age buyers (25-44 years old) in low- (blue) and high-price MSAs (red). The dashed line depicts the economywide average. Right panel: changes in the same variables, normalized to 1 in 2006. Gray bands indicate NBER recessions. Source: ACS, Zillow.

Other Sources of Variations in Home Ownership

Entry vs. exit margins One possibility is that loan applications and rejections varied across MSAs for reasons unrelated to underwriting standards, for instance because local banks were more exposed to the Great Recession and thus more likely to reject applications, all else equal. My model results shows that even in the absence of such variations, the mere tightening of national credit standards had heterogeneous effects on mortgage issuances and home ownership. Figure 24 in Appendix further explores this possibility using loan-level data on all mortgages originated (from the Home Mortgage Disclosure Act, HMDA). Loan application rates decrease across MSAs, persistently, and more in high price MSAs, where they were higher before the bust. In contrast, rejection rates spike in 2007 but fall and remain stable during the recovery. The same is true of foreclosure rates (RealtyTrac data). The decrease in loan applications thus seems more likely to explain low home ownership during the 2010s. These results can be read as nuancing Piskorski and Seru (2018) and Gilchrist et al. (2018), who respectively focus on foreclosures and banks' credit supply shocks.

Figure 24: Loan application rate, rejection rate, foreclosure rate by region



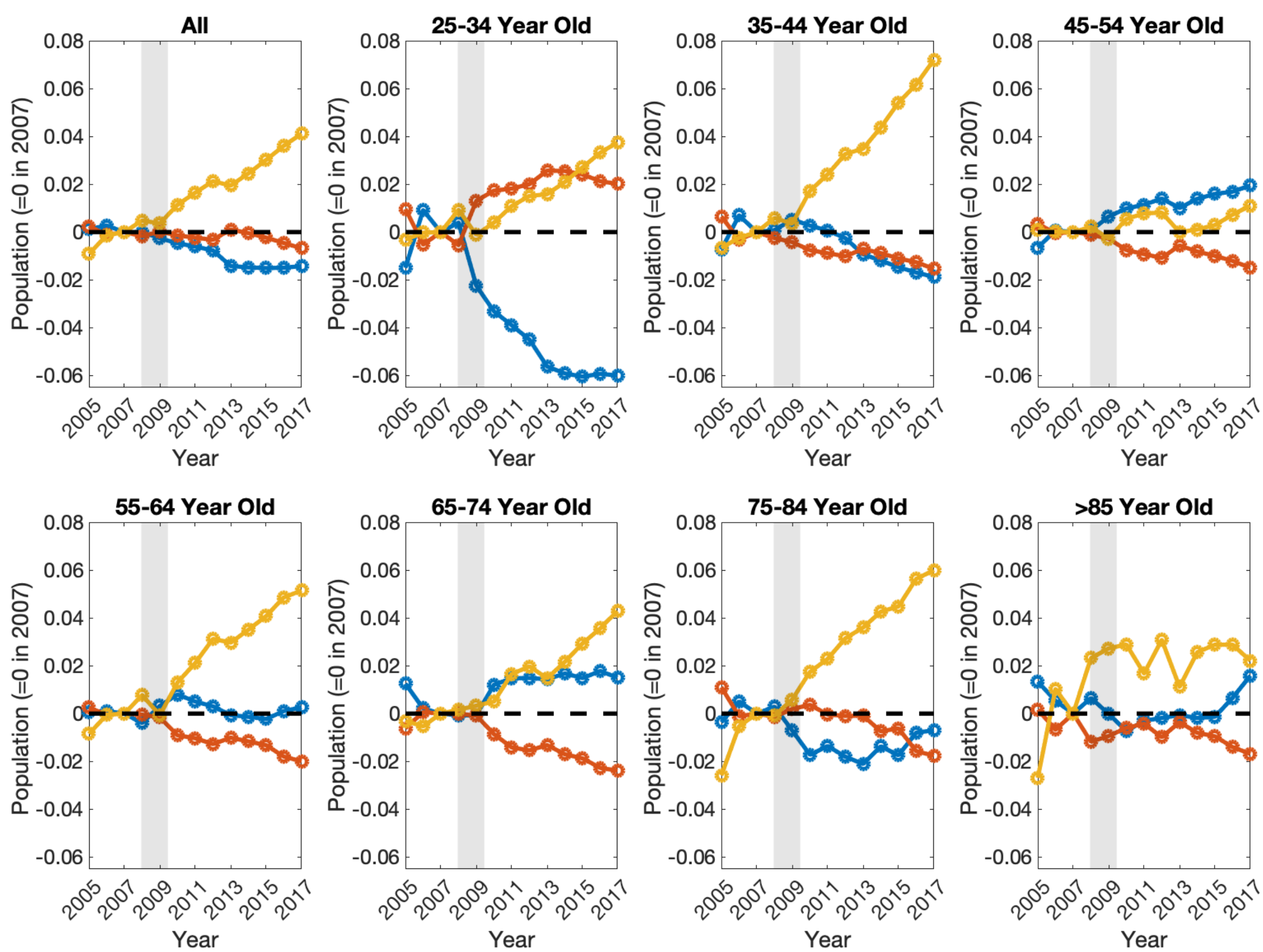
Source: HMDA, RealtyTrac, Zillow.

Agency vs. PLS mortgages My result on credit standards is for GSA loans. Private label securitized mortgages (PLS) have also been shown to affect housing booms and busts (Justiniano, Primiceri and Tambalotti (2017), Mian and Sufi (2019)), and could drive changes in first-time mortgage originations, instead of the aggregate credit shock to LTV and PTI requirements on which focus. Using the CCP/Equifax data, I calculate that GSE and FHA loans represent 50% to 90% of first-time mortgage originations in 2000-17, and that this is therefore unlikely to be the case. Over time, in 2005-06, the decrease in the number of first-time mortgages is entirely driven by GSE mortgages, then entirely by PLS mortgages in 2006-2007, then equally by both in 2008-2011. Reinforcing my point, Mian and Sufi (2019) report that almost 100% of the relative increase in transactions in areas reliant on PLS mortgages was driven by speculators, not first-time buyer.

A.8 Measuring Changes in MSA Population in 2007-2017

The ACS metro to metro migration data, which is aggregated into chunks of 5 year periods, makes it difficult to measure these flows. To do it, I instead directly use the average population size in each group of regions. In each region and in the aggregate, I normalize the time series of average population sizes by its 2007 value such that it is equal to 1 in 2007. I then subtract the aggregate time series to obtain regional population series which are now normalized to 0 in 2007.

Figure 25: Population Changes in 2005-2017 by MSA Group



Notes: Changes are calculated as deviations from their 2007 values, normalized to 1, to which the average trend, normalized to 1 in 2007 too, is subtracted to control for the increase in overall population. The resulting plotted series are in deviation from their 2007 value net of the trend, normalized to 0. MSAs are sorted into three groups by the recovery speed of house prices, from slowest (bottom 25%, blue) to fastest (top 75%, yellow). Within each group, the weighted average rate of a given age group is calculated using the MSA total population in 2007. The shaded area indicates the NBER recessions. Data source: Zillow, ACS.

B Model Details

B.1 Households

Pension schedule The pension schedule of Guvenen and Smith (2014) replicates the U.S. pension system and relates last period income to average income over the life-cycle to compute retirement benefits. Denote the economywide average lifetime labor income as $\overline{Y}$, and household i's relative lifetime income as $\tilde{Y}_{i,R} = \widehat{Y}_{i,R}/\overline{Y}$, where $\widehat{Y}_{i,R}$ is the predicted individual lifetime income implied by a linear regression of i's lifetime income on its income at retirement age.[52] Retirement income is equal to:

$$Y_{i,R} = \overline{Y} \times \begin{cases} 0.9\tilde{Y}_{i,R} & \text{if } \tilde{Y}_{i,R} \leq 0.3 \\ 0.27 + 0.32(\tilde{Y}_{i,R} - 0.3)\tilde{Y}_{i,R} & \text{if } 0.3 < \tilde{Y}_{i,R} \leq 2 \\ 0.81 + 0.15(\tilde{Y}_{i,R} - 2)\tilde{Y}_{i,R} & \text{if } 2 < \tilde{Y}_{i,R} \leq 4.1 \\ 1.13 & \text{if } 4.1 \leq \tilde{Y}_{i,R} \end{cases} \tag{35}$$

B.2 Housing Supply: Discussion

In the baseline model, the supply of rentals is held by absentee landlords with perfectly inelastic portfolios, so $\left\{ho_j^{sqft}\right\}$ are fixed across regions. Importantly, while the fraction of owner-occupied *square feet* is exogenous, the homeownership *rate* among households is fully endogenous. House price variations induce changes in the housing stock $H_{j,t}$ through residential investment $I_{j,t}$, hence in the number of owner-occupied square feet $H^{ho}_{j,t}$. Because the size of owner-occupied units $\overline{h}$ is fixed, variations in $H^{ho}_{j,t}$ induce variations in the homeownership rate among households. In equilibrium, house prices will adjust to induce just enough households to hold the stock of owner-occupied houses. This assumption makes the model tractable, and despite this simplification, the main experiment closely replicates the change in homeownership in the data during the 2010s.[53] One limitation of this assumption is that it does not allow to capture changes in landlords'

[52]Using income retirement to define pension benefits allows to save a state variable in the dynamic programming problem.

[53]Intuitively, the decrease in homeownership rates is due to a decrease in residential investment because prices fall. Combined with the depreciation of the total housing stock, this implies that less square feet are available for owner-occupied houses. Under the fixed housing size $\overline{h}$, this implies that the fraction of owners must decrease in equilibrium.

welfare arising from changes in prices.[54]

The assumption of no conversion between owner-occupied houses and rentals implies that negative shocks to households' demand for owner-occupied units will result in a decrease in prices. Rather than an increase in conversions from owner-occupied houses to rentals and no price decrease, which would happen if landlords' demand for houses exactly compensated the decrease in households' demand (Greenwald and Guren (2019)). My model shares this feature with Favilukis et al. (2017). It addresses some of the criticisms of their framework by Kaplan et al. (forthcoming) by having rentals and credit constraints only applying at origination.

B.3 Housing Ladder: Discussion

Modeling a housing ladder is likely to reduce the tractability of the model without changing the transmission channel of credit shocks through young buyers. For a credit shock to have a large effect on households' demand, it must be that they do not currently own a house which they could sell to reduce their mortgage balances. This would be true even if buyers could choose from different housing sizes. Repeat buyers, who want to buy a different size than their current one, must sell their current home, so they need to borrow less, and are less likely to be affected by credit shocks. Selling their home increases their down payment so the LTV constraint is less likely to bind, and since they need to borrow less the PTI constraint is less likely to bind too. Thus the important assumption is that households cannot own multiple homes. If there are different sizes, my results would hold if those markets segmented, i.e. it is impossible to convert two houses of sizes $h = 1$ and $h = 2$ into a single house $h = 3$.

Finally, if anything, the findings of Ortalo-Magné and Rady (2006) suggest that adding a housing ladder would *amplify* the effect of first-time buyers on housing markets, through capital gains and losses experienced across the ladder as prices vary.

[54]Under the assumption that ho_j^{sqft} is a function of the price which is homogeneous of degree $k \geq 0$, the solution method that I develop could be applied directly, and it would be straightforward to assume that the fraction of square feet of the housing stock devoted to owner-occupied houses varies over the cycle. In particular, there would be more conversions to rentals when prices are low relative to rents, reflecting landlords' incentives to buy more of the housing stock to rent it out to households. However, it would make the baseline model less transparent, while still abstracting from the welfare effects of price movements on landlords.

B.4 Model Solution

Steady state Start by normalizing $\overline{h} = 1$, and fix the parameters δ, ρ_j, which are directly measured in the regional panel constructed earlier. In steady state, the model is solved in three steps. First, fix p_L^* and p_H^* to match the regional distribution of house prices in the data.

Second, choose rents R_L^*, R_H^* to match homeownership rates in the data, $ho_L^{hh}(\mathbf{P}^*, \mathbf{R}^*)$ and $ho_H^{hh}(\mathbf{P}^*, \mathbf{R}^*)$. For given local prices, they are increasing in local rents. Provided migration rates are low, R_L and R_H can be separately chosen in regions L and H. Simultaneously, choose regional amenity benefits, χ_j, to match the regional distribution of price to rent ratios. Homeownership rates in the model are obtained by solving the household's problem with a global nonlinear solution method, computing the stationary distribution of households, and aggregating it across regions and tenure groups.

Third, R_L^*, R_H^* generate regional demands for rentals, $\int_{\Omega^{rj}(\mathbf{P}^*, \mathbf{R}^*)} h_j(\mathbf{P}^*, \mathbf{R}^*)\, d\lambda$. Given those, the market-clearing conditions can be inverted to solve for the regional parameters ho_j^{sqft} and $\overline{I}_j$ in closed form:

$$ho_j^{sqft} = \frac{\frac{\overline{h} ho_j^{hh} pop_j}{\int_{\Omega^{rj}} h_j d\lambda}}{1 + \frac{\overline{h} ho_j^{hh} pop_j}{\int_{\Omega^{rj}} h d\lambda}} \quad \text{and} \quad \overline{I}_j = \frac{\delta \overline{h} ho_j^{hh} pop_j}{ho_j^{sqft} p_j^{\rho_j}}. \tag{36}$$

Given the new ho_j^{sqft} and $\overline{I}_j$, go back to choosing R_L^*, R_H^* and χ_j to match homeownership rates and price to rent ratios, and iterate until convergence. Intuitively, (i) local housing supply restrictions $\overline{I}_j$ mostly affect prices p_j through the scarcity of the housing stock; (ii) the fraction of owner-occupied square feet ho_j^{sqft} mostly affect homeownership rates among households ho_j^{sqft} by restricting the supply of houses available to owners; (iii) amenity benefits χ_j mostly affect the price to rent ratios p_j/R_j because they alter the trade-off between owning and renting.

Dynamics of the regional distribution of prices I assume that households' value functions are subject to i.i.d. idiosyncratic taste shocks following a type I Extreme Value distribution. Appendix I provides details on the computations. I borrow this assumption from the dynamic demand literature in IO (Diamond, McQuade and Qian (2019) illustrate an IO application in the context of a housing model). Given value functions, it allows to compute closed forms for transition probabilities between discrete choices and for the expectations of continuation value functions, which are smooth functions of prices. This feature is essential to solve for the dynamics of prices and rents in response to unanticipated shocks, without generating jumps in marker-clearing conditions. Finally, I rewrite the model with a cash-on-hand state variable, which is restricted to be positive, and eases the computations.

B.5 Life-Cycle Profiles: Sorting and Population Distribution

Sorting implies regional heterogeneity in life-cycle profiles (Figure 26). Some households move to low price MSAs in their twenties because they are more affordable, and move back to high price MSAs in their thirties, once their income is higher and they have accumulated savings.

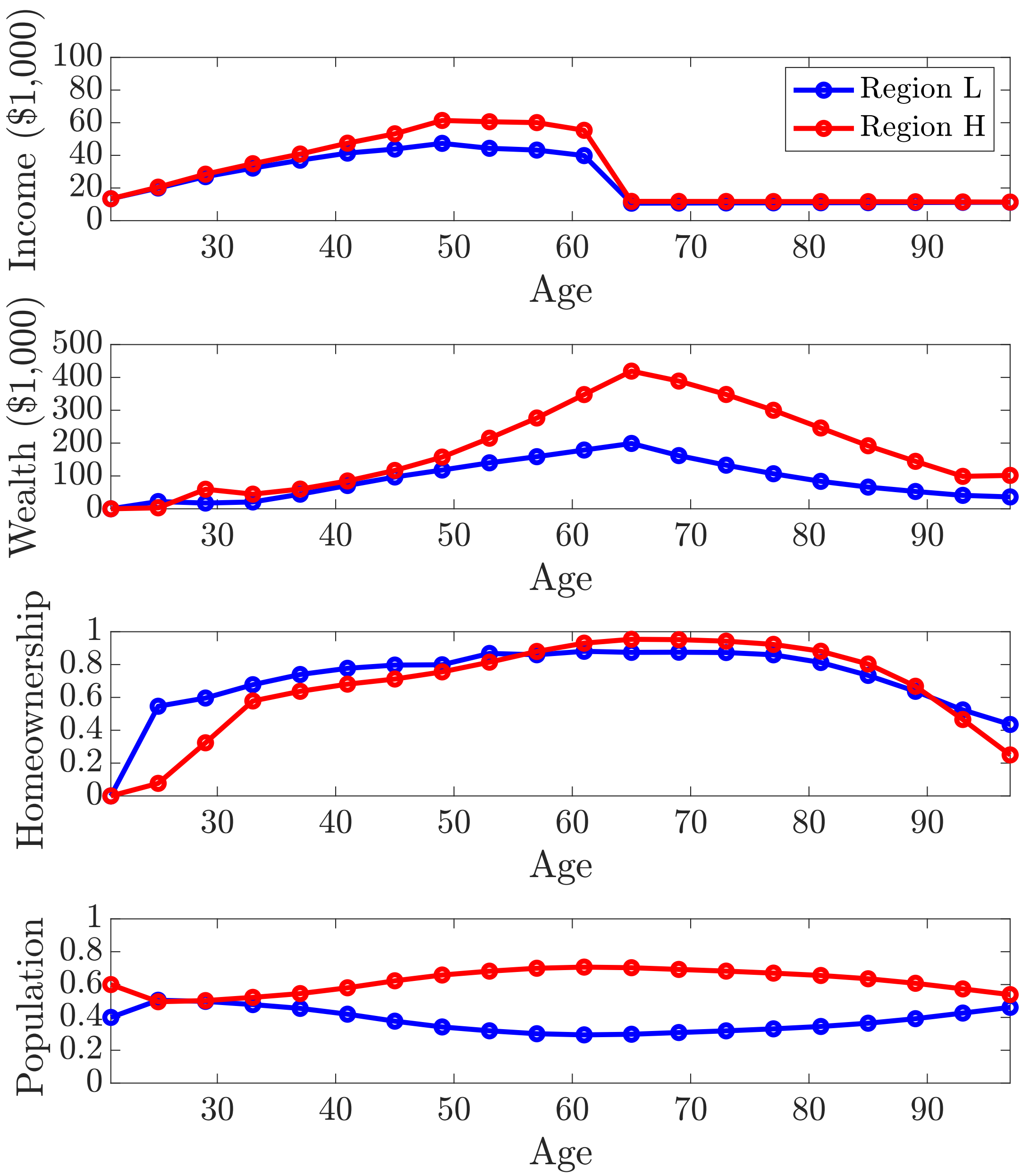
Figure 27 plots steady state migration rates by income groups and region to provides more details on population movements. Like in the data, younger households are more likely to migrate.[55] The model implies that among those, more productive ones are more likely to migrate.[56] Finally, renters have a higher migration rate than owners because they tend to be younger and do not need to pay the seller's transaction cost f_s when migrating.[57]

[55]From Table 17 of the ACS in 2006-07 for Metropolitan Mobility of Persons 16 Years and Over, by Sex, Age, Race and Hispanic Origin, and Labor Force Status, I calculate for instance that 16-24 year old respondents are 40% more likely to move than 25-64 year olds (with average mobility rates of 2.75% versus 1.99%), and 280% more likely to move than 65+ year olds (0.72%).

[56]While average migration rates between metros (*across* ages) are slightly decreasing with income (see Table 22 from the same source in the ACS), there is evidence of higher moving rates among college-educated households. The model matches this fact that *within* younger age categories, more productive individuals are more likely to move, as e.g. described for the recent period in accounts such as "How migration of Millennials and seniors has shifted since the Great Recession" (*Brookings*, January 31, 2019), and "Migrant Millennials are redrawing the map of America" (*Financial Times*, June 26, 2018).

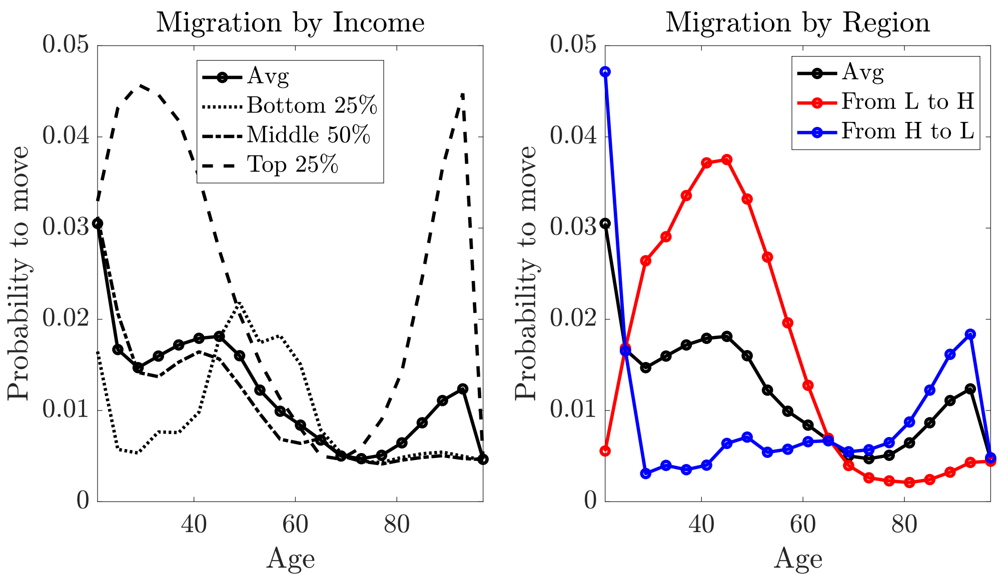
[57]During the transition, there is also a "lock-in" effect of home ownership, whereby owners are reluctant to sell their house at lower prices and choose to not move (Karahan and Rhee (2019).

Figure 26: Regional life-cycle profiles of labor income, wealth, home ownership, and population shares by region



Notes: Household life-cycle profiles from 21 to 95 years old. Upper panel: gross annual labor income (including pensions) in thousands of 1999 dollars. Upper middle panel: wealth (including housing) in thousands of 1999 dollars. Lower middle panel: home ownership rate. Lower panel: regional population shares.

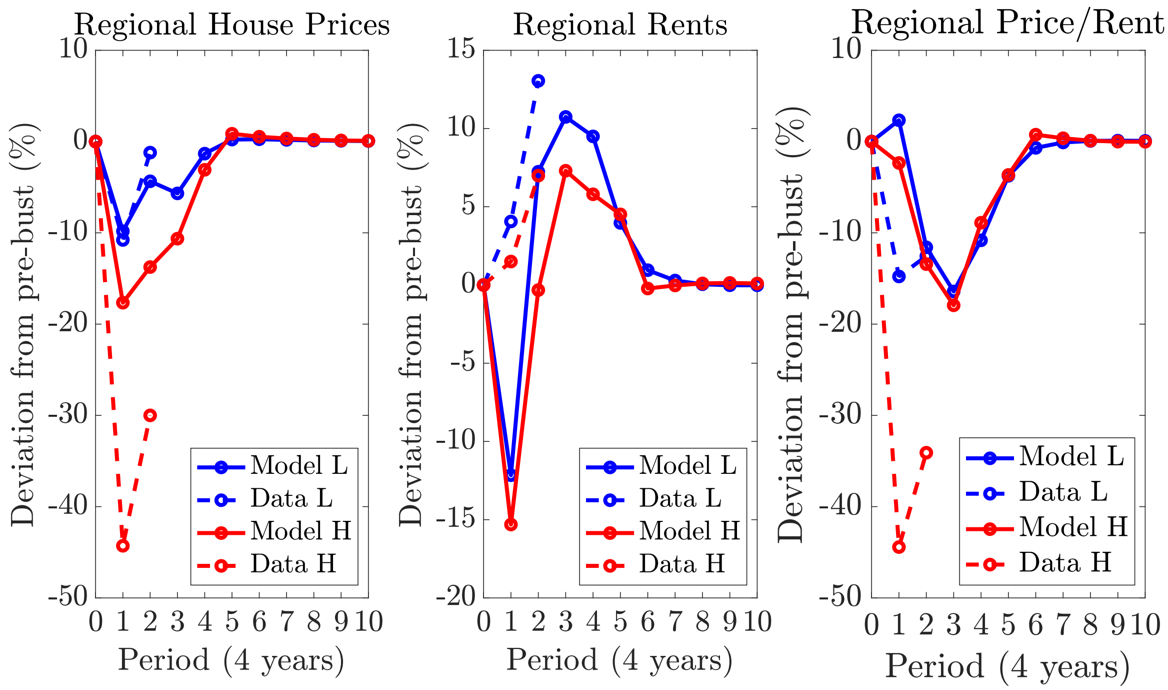
Figure 27: Life-cycle profiles of migrations in steady state



Notes: Household life-cycle profiles of steady state migration rates from 21 to 95 years old. Left panel: for the average (solid line), bottom 25% (dotted), middle 50% (dotted-dashed) and top 25% (dashed) of the productivity distribution economywide. Right panel: average, from low to high price MSAs (red), from high to low price MSAs (blue).

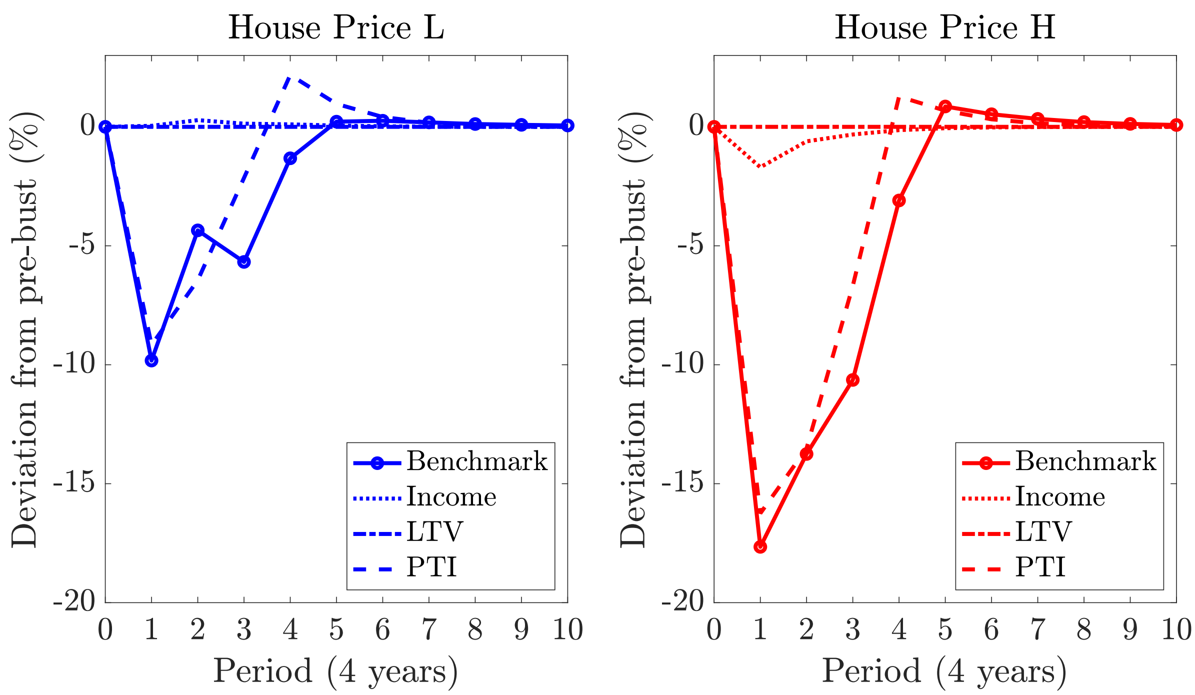
C Model Results: Response to Income and Credit Shocks

Figure 28: Response of Regional and Aggregate House Prices, Rents, and Price to Rent Ratios to an Aggregate Recession



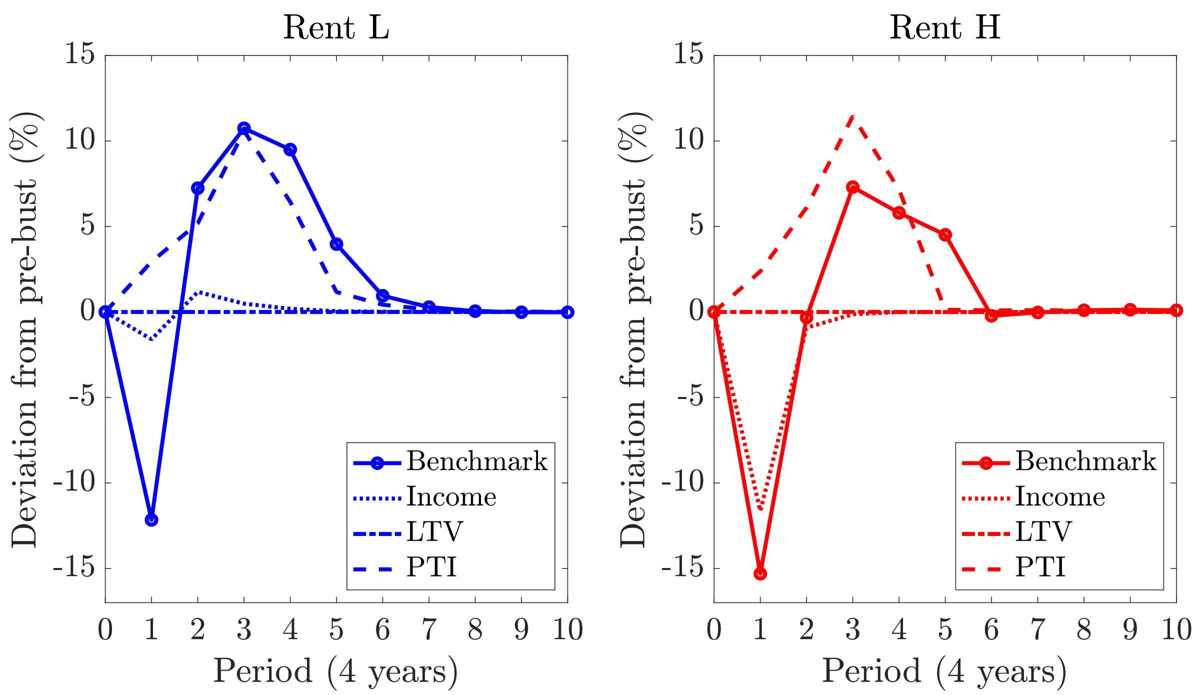
Data sources: Zillow, BLS. Changes in percentage terms relative to the pre-bust period (2006).

Figure 29: House price responses to separate negative shocks to income and mortgage credit standards



Notes: Changes in percentage terms relative to the pre-bust period (2006).

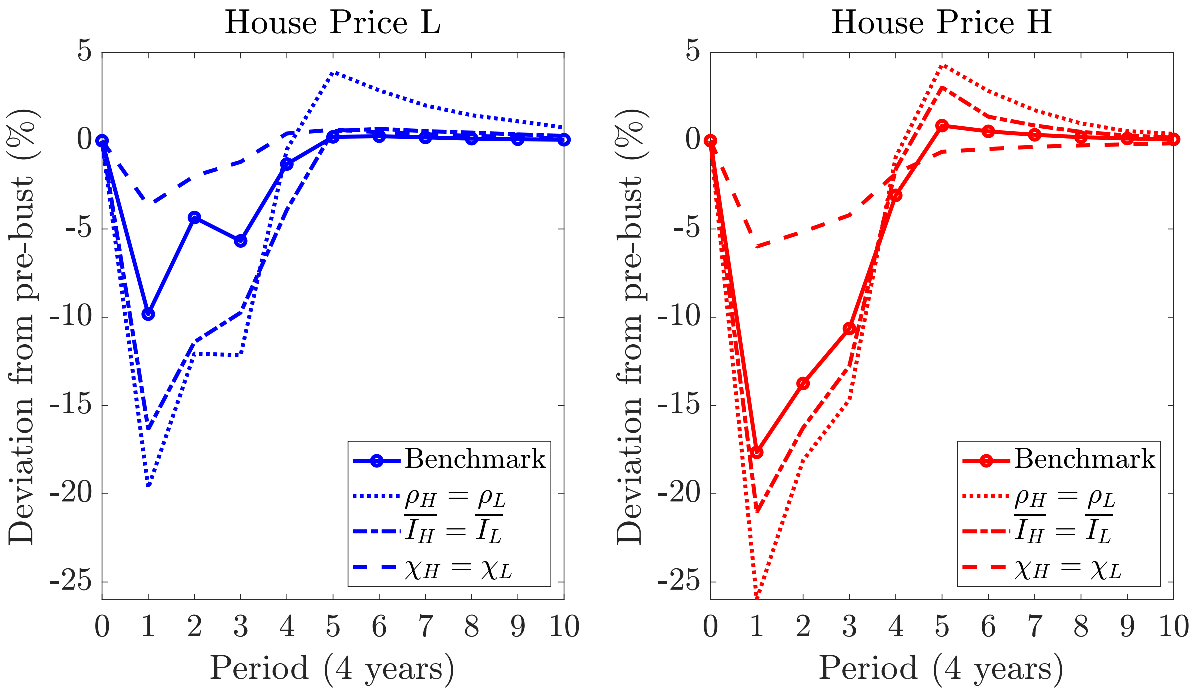
Figure 30: Response of regional rents to separate negative shocks to income and credit standards



Notes: Data sources: Zillow, BLS (to construct rents prior to 2010).

D Model Results: Housing Markets Primitive Parameters

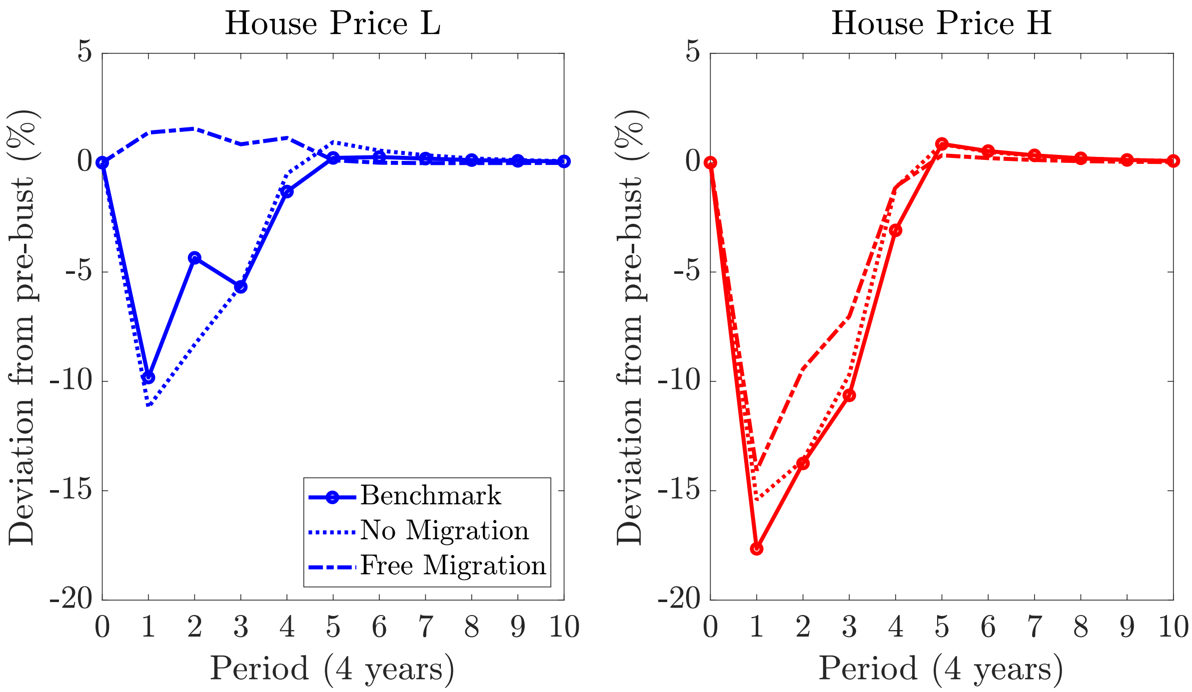
Figure 31: Sensitivity of house price responses to housing markets primitive parameters



Notes: Changes in percentage terms relative to the pre-bust period (2006).

E Model Results: Millennial Cohorts

Figure 32: Sensitivity of house price responses to initial conditions of the cohort of young buyers



Notes: Changes in percentage terms relative to the pre-bust period (2006).

In an extension, I will study two additional characteristics of Millennials. First, their large cohort size, by embedding the mechanism of Mankiw and Weil (1989) into my structural model, whereby demographics affect housing markets by changing the measure of individual demand curves which are aggregated in market-clearing conditions. Second, the possibility that they have a lower preference for home ownership (Choi, Zhu, Goodman, Ganesh and Strochak (2018)), potentially owing to "scarring" effects as in Malmendier and Nagel (2011).

F Welfare gains from policies

Let $V(s, S_b)$ be the value function of a household with individual state $s = (e, b, t, l, a)$ (endowment, net asset position, tenure status, location, age) and when the aggregate state is S_b, the benchmark economy *without* policy. Let $V(s, S_p)$ be the value function of the same household type when the aggregate state is S_p, the benchmark economy *with* policy.

Now define the *one-period consumption equivalent variation* (CEV) $\omega(s)$ for this household as the one-time increase in current consumption in the benchmark economy S_b that makes the household indifferent between living in S_b and living in S_p, the economy with policy. $\omega(s)$ is implicitly defined by the following equality:[58]

$$V(s, S_p) = \frac{u((1+\omega(s))c(s,S_b),(1+\omega(s))h(s,S_b))^{1-\gamma}}{1-\gamma} + \chi(s) + \beta\mathbb{E}\left[V(s', S_p)\,|s\right] \tag{37}$$

Solving for $\omega(s)$ using the definition of $V(s, S_b)$ gives:

$$\omega(s) = \left(\frac{V(s,S_p) - V(s,S_b) + u_b}{u_b}\right)^{\frac{1}{1-\gamma}} - 1 \tag{38}$$

where $u_b = \frac{u(c(s,S_b),h(s,S_b))^{1-\gamma}}{1-\gamma}$.

To compute it in steady state and over transitions, I keep track of value functions $V(., S_b), V(., S_p)$ and policy functions $c(., S_b), h(., S_b)$ (for owners, we simply have $h(., S_b) = \overline{h}$), and use the definition of u.

I use this measure of welfare changes rather than permanent CEV because the latter do not have comparable interpretations for young and old households in OLG model, given that young households expect to live for more periods. This measure is e.g. used by Hur (2018). Alternatively, computing permanent CEV would require to use a numerical nonlinear solver for ω, since the homogeneity of the CRRA function cannot be used with additive amenity benefits χ to compute ω as a transformation of the ratio of value functions in S_b and S_p, as is usually done. This is computationally feasible for steady state CEV, but untractable for the transitions.[59]

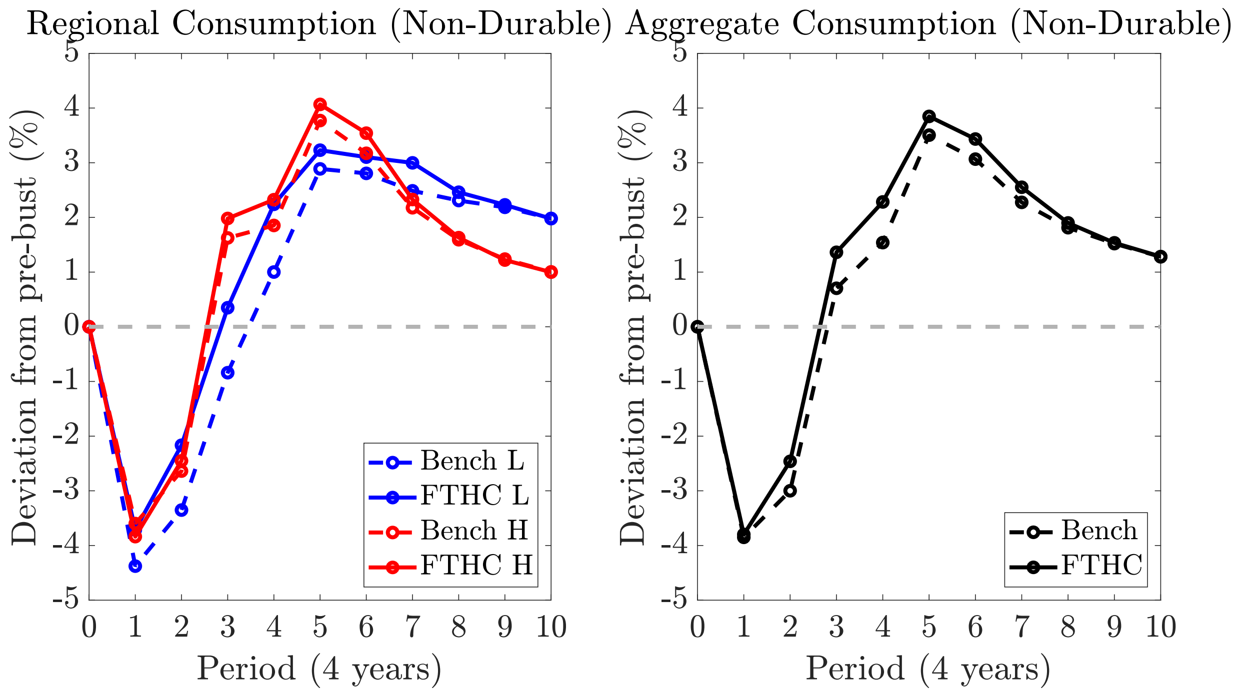
Then, average CEVs for a given household type can be computed using the marginal distributions of $\lambda(s)$.

[58] It is defined as increasing the consumption of both non-durable goods and housing services here.

[59] An alternative would be to used multiplicative amenity benefits, increasing the value of consumption depending on tenure and location status. In that case permanent CEV can be solved for as usual, as a transformation of the ratio of value functions in S_b and S_p. However the calibration is more difficult because amenity benefits are now raised to the power $1-\gamma$, and must take very high values in the H region to simultaneously generate a high price to rent ratio and population share.

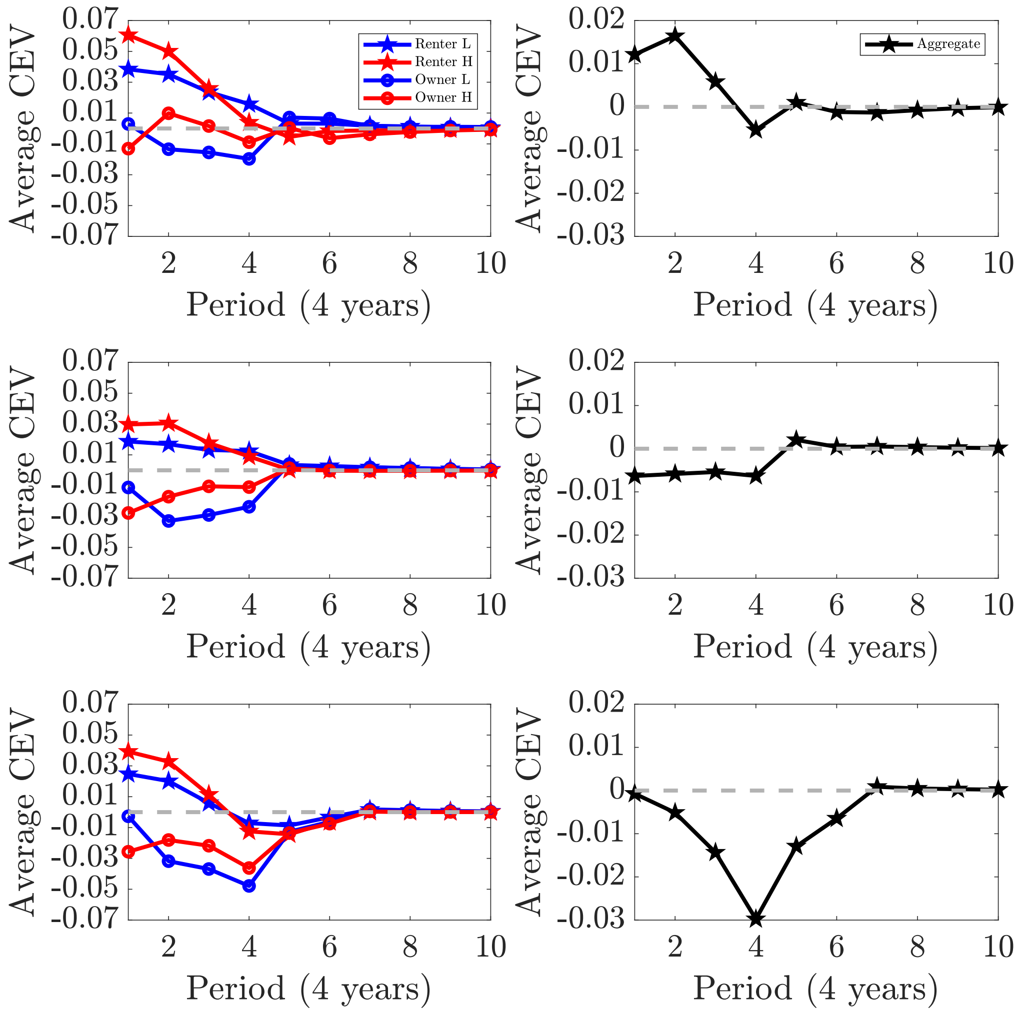
G Policy Results

Figure 33: Effect of the FTHC on consumption



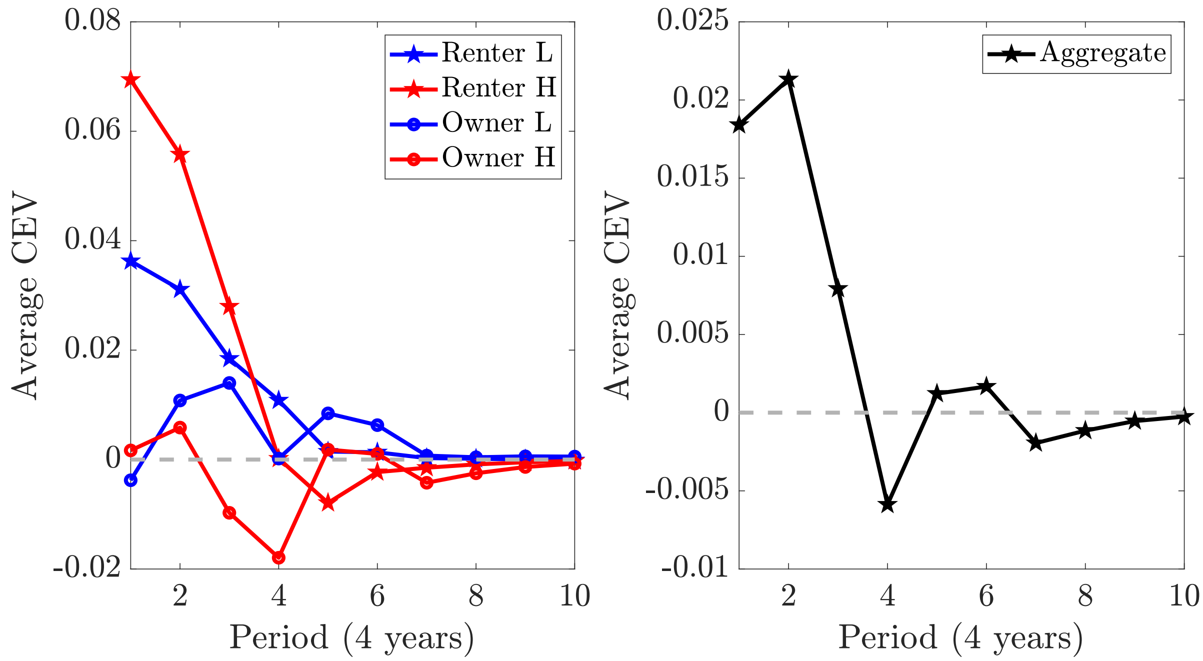
Notes: Policy not financed.

Figure 34: Welfare effects of the FTHC under different financing scenarios



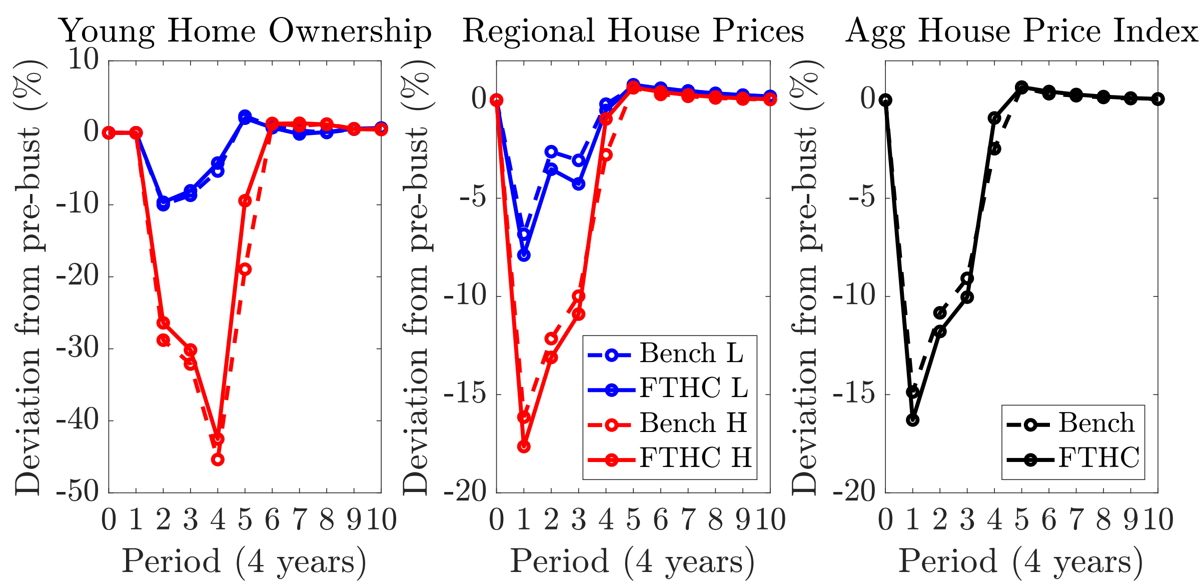
Notes: Upper panels: FTHC policy not financed. Middle panels: financed at the time it is implemented. Lower panels: financed one period (four years) after it is implemented. Left panels: consumption equivalent variations (in terms of four year consumption) for the average renter and the average owner in each region. Right panels: average consumption equivalent variations (in terms of four year consumption) for the average household in the economy.

Figure 35: Welfare effect of a place-based FTHC policy



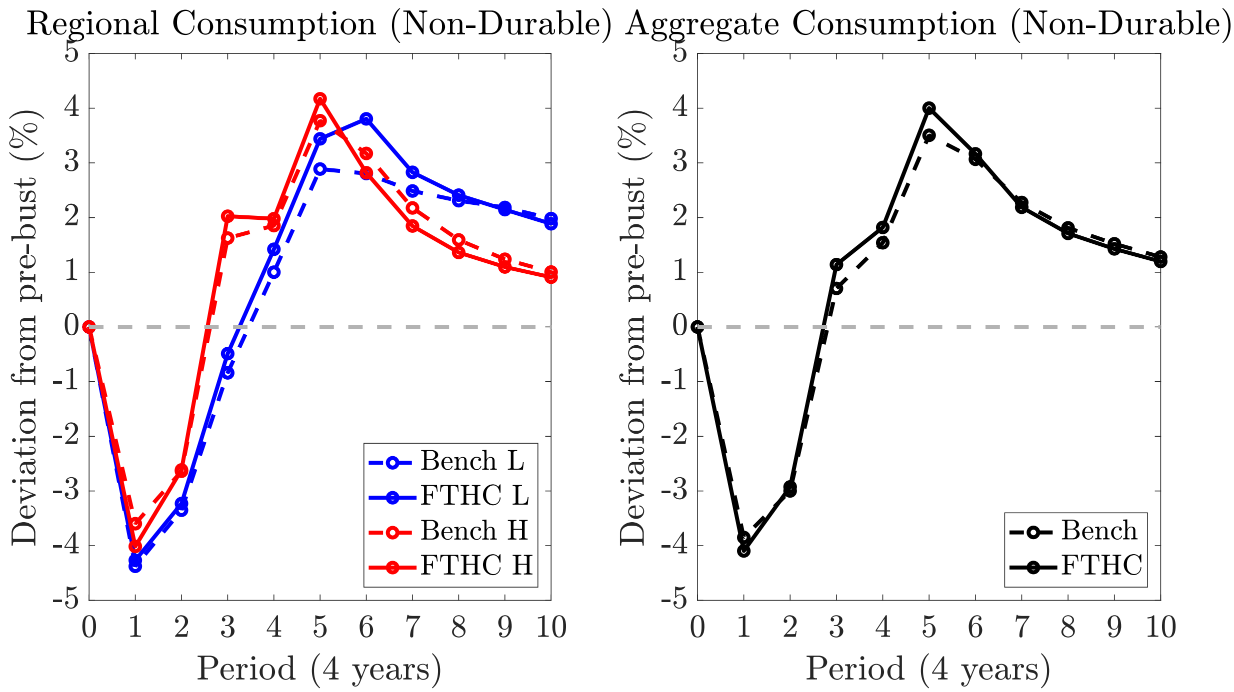
Notes: Average consumption equivalent variations (in terms of four years of non-durable consumption) for the average household in the economy. Solid line: FTHC policy not financed. Dashed line: financed at the time it is implemented. Dotted line: financed one period (four years) after it is implemented.

Figure 36: Credit relaxation policy (PTI requirement +5 pp): effect on home ownership and house prices



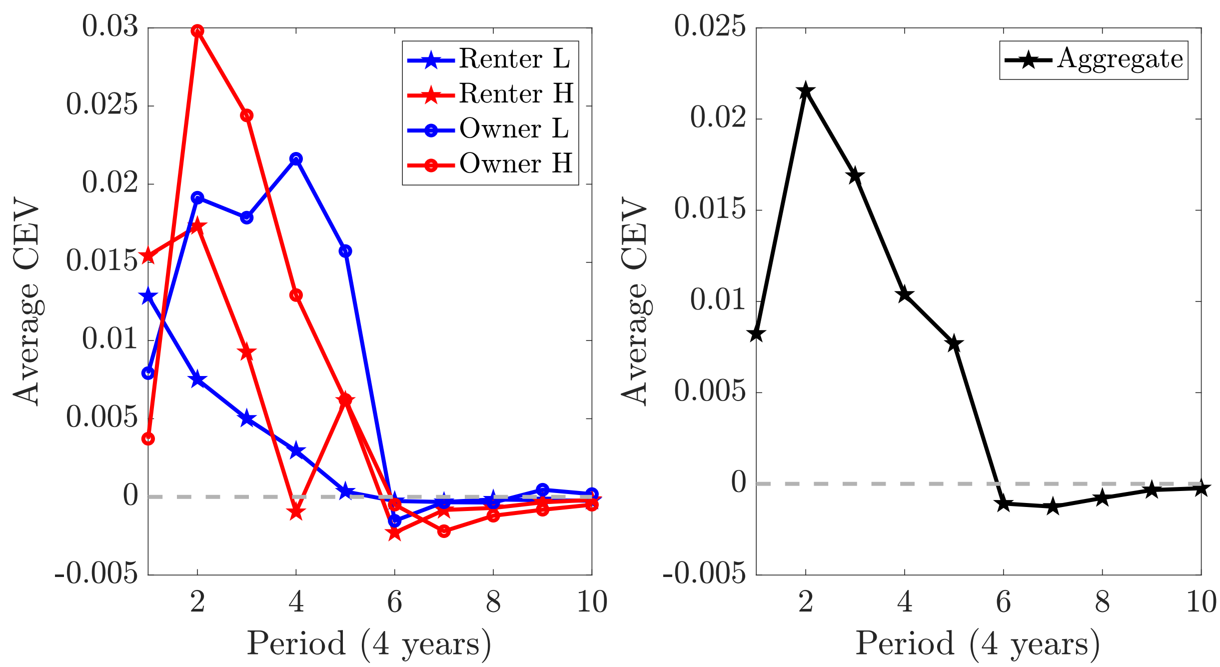
Notes: Changes in percentage terms relative to the pre-bust period (2006).

Figure 37: Credit relaxation policy (PTI requirement +5 pp): effect on consumption



Notes: Changes in percentage terms relative to the pre-bust period (2006).

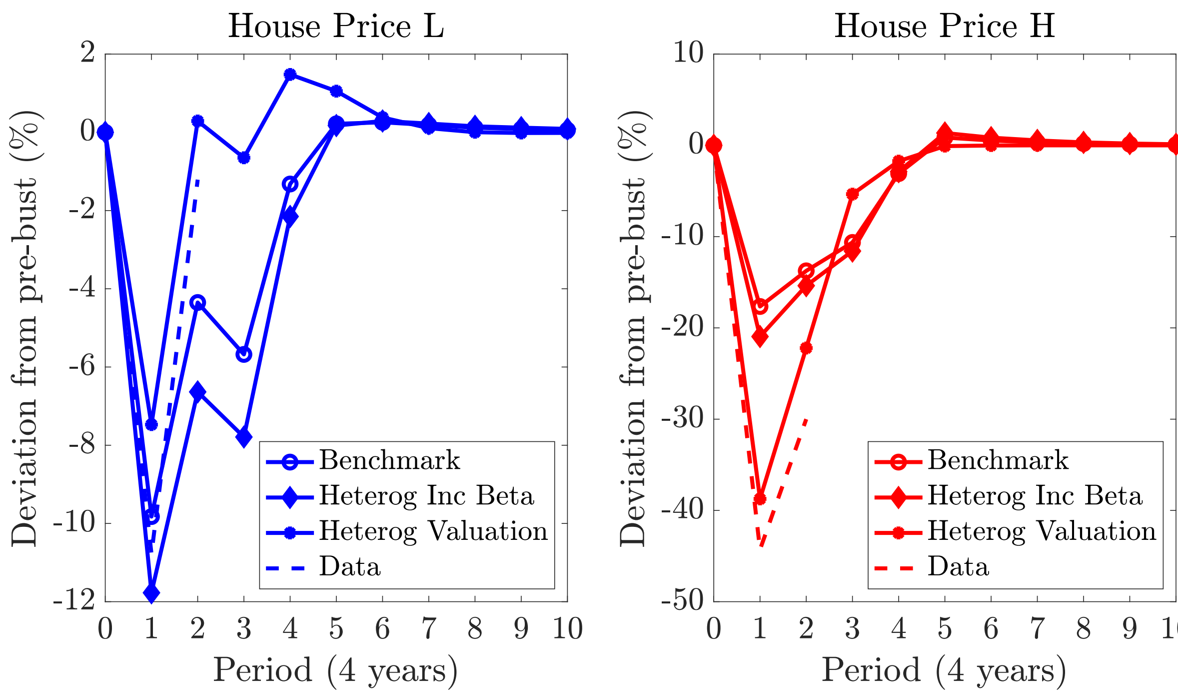
Figure 38: Credit relaxation policy (PTI requirement +5 pp): welfare effect



Notes: Changes in percentage terms relative to the pre-bust period (2006).

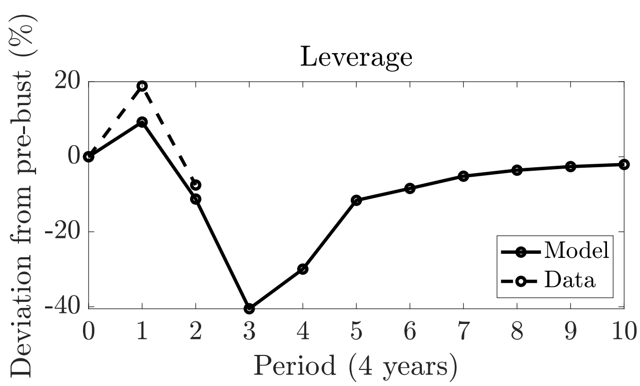
H Extended Model: Local Shocks and Mortgage Default

Figure 39: House prices under the different models: benchmark, with regional exposures to aggregate income shocks, and with regional shocks to households' housing valuations (allowing for mortgage default)



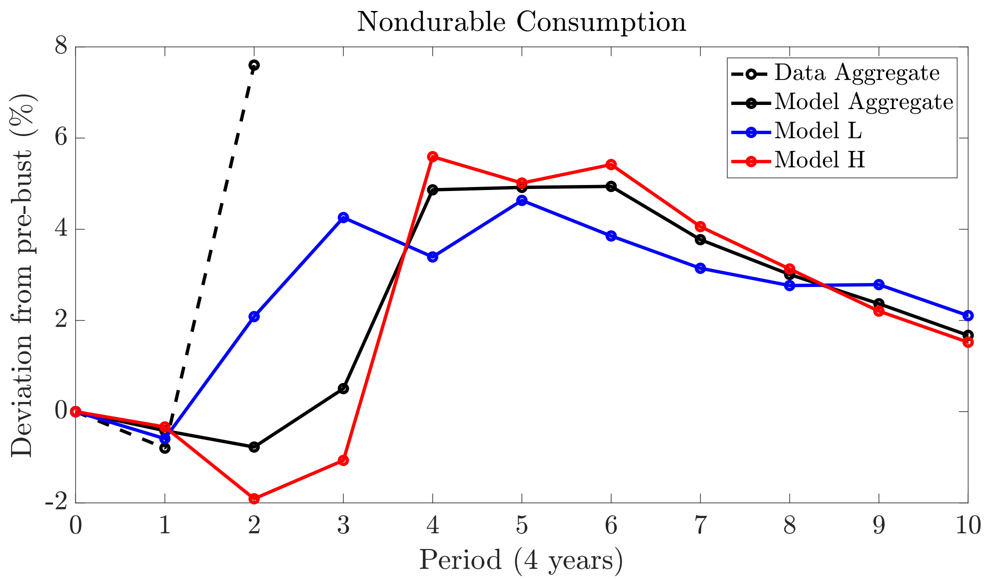
Data source: Zillow. Changes in percentage terms relative to the pre-bust period (2006).

Figure 40: Leverage response to the recession



Notes: Leverage is computed as total mortgage debt outstanding to total housing value.

Figure 41: Nondurable consumption response to the recession



Data source: Real Personal Consumption Expenditures for Nondurable Goods (U.S. Bureau of Economic Analysis). Changes in percentage terms relative to the pre-bust period (2006).

I Computational Appendix

The steady state takes 10 seconds to compute. The transition dynamics takes 15 minutes to compute, when parallelized on the NYU high-performance cluster using 20 cores with 28GB of memory each.

I.1 State Variable's Transformation

I use the cash in hand variable $m_{j,t} = p_{j,t}\overline{h}_j + (1+\tilde{r}_t)b_t$ for owners and $m_{j,t} = (1+r)b_t$ for renters, which is always positive. The grid is the same for $j = 1, 2$.

I.2 Logit Error Taste Shocks

For the computations, I assume that the value of each option of the discrete choice problem is subject to an idiosyncratic logit error taste shock. For instance, the value of renting in region L is equal to The value of being a region L renter is:

$$\tilde{V}^{rL}(a, b_t, y_t) = V^{rL}(a, b_t, y_t) + \tilde{\varepsilon}^{rL}(a, b_t, y_t) \tag{39}$$

where $\tilde{\varepsilon}$ follows a type I extreme value (Gumbel) distribution with location parameter 0 and scale 1.

It allows:

(i) To smooth out the computation of the expectation of the continuation value function, which is the envelope value of the options available next period, given the household's current state (not the same options are available for owners and renters in the various zones). It smooths out policy and value functions, and makes them more monotonic with respect to prices. This allows to reduce the size of the state space, otherwise many grid points are needed. The expectation of the envelope value has a closed form, for instance for region L renters:

$$\mathbb{E}_{L,t}\left[V^r\right] = \mathbb{E}_{L,t}\left[\int \tilde{V}^r \mathbf{dF}\left(\tilde{\varepsilon}\right)\right] = \mathbb{E}_{L,t}\left[\log\left(\sum_{j=1}^{4} e^{\tilde{V}^{r,j}}\right)\right] \tag{40}$$

where $\tilde{V}^r = \max\left\{\tilde{V}^{r,j}\right\}_{j=1,...4}$. The outside expectation $\mathbb{E}_{L,t}\left[.\right]$ is taken over the distribution of idiosyncratic income shocks (in the benchmark model they are identical across regions). V^r now denotes the "ex-ante value functions", after integrating over the vector of idiosyncratic errors (there is one realization for each individual – state – and option).

(ii) To obtain closed-form for the probabilities of choosing the various options. Those are useful when computing the transition matrix for the law of motion of the cross-sectional distribution over location $\times$ tenure $\times$ income $\times$ cash-in-hand, which I approximate with a histogram. The probabilities have the multinomial logit closed-form, for instance:

$$\Pr\left(\tilde{V}^{r,j} = \tilde{V}^{r}\right) = \frac{e^{\tilde{V}^{r,j}}}{\sum_{j'=1}^{4} e^{\tilde{V}^{r,j'}}} \tag{41}$$

(iii) Compute the dollar cost of policies in closed-form.