The Missing Home Buyers: Regional Heterogeneity and Credit Contractions *

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Abstract

This paper demonstrates that the protracted decrease in young homeownership since the Great Recession was driven by high-house price regions, despite credit standards changing mostly nationally. Using a panel of U.S. metro areas, I calibrate an equilibrium spatial macro-finance model with overlapping generations of mobile households. Aggregate and regional housing dynamics are explained more by the heterogeneous impacts of an aggregate credit tightening than by local shocks. Lower Millennial income and wealth amplify this effect. The impact of subsidies to first-time buyers is dampened, because they fail to stimulate regions that suffer larger busts. Place-based subsidies achieve larger gains.

JEL classification: E21, G11, G21, G51, J11, R30
Keywords: Spatial macro-finance, home ownership, first-time buyers, mortgages, credit standards, house prices, Millennials

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1 Introduction

Housing busts, like many recessions, affect demographic groups very differently. After the Great Recession, *young* home ownership fell deeply and persistently, leaving many Millennial buyers excluded from the housing market and leading to a large decline in total home ownership (Figure 1). This decrease, equivalent to 7.6 million missing purchases in the United States, has attracted widespread attention as it entails a potential shift in the importance of housing on households' balance sheets.[1]

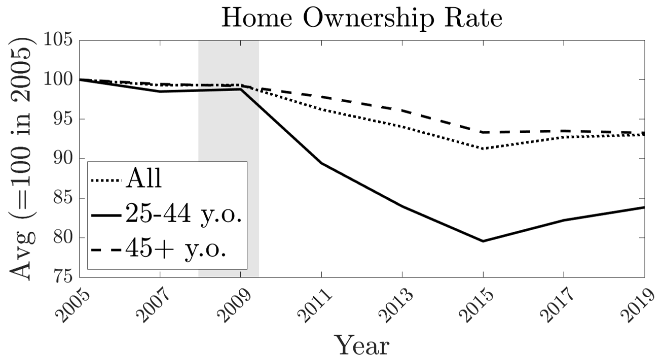
While existing work has focused on heightened exit from home ownership through foreclosures (Mian and Sufi (2009), Adelino, Schoar and Severino (2016)), less is known about its decrease through the lower *entry* of young buyers, which represent 50% of new purchase mortgages. Especially puzzling is that it coincided with a large dispersion in house price busts between regions (Piskorski and Seru (forthcoming)) – in frictionless models of asset market participation, entering buyers should arbitrage price differences away. This paper studies the causes of lower entry into home ownership from young buyers and its consequences for housing markets. I calibrate a new macro-finance model of the cross-section of housing markets to U.S. household-level and regional panel data, and address two questions: (i) How do changes in households' environment (period effect) and differences between cohorts (cohort effect) account for this shift? (ii) What do they imply for stimulus policies targeting first-time buyers?

My results highlight the importance of regional heterogeneity for credit contractions. I find that the decrease in young home ownership can be traced back to house price differences between regional housing markets, which amplified the nationwide tightening of credit standards through regionally-binding borrowing constraints (period effect). Young buyers' access to home ownership is largely determined by credit because of the upward-sloping life-cycle profile of income and wealth, especially for Millennials entering the economy in worse times (cohort effect). Because they are more constrained in areas with higher prices and often fail to move between regions, they postpone buying more when credit contracts, leading in turn to larger price declines. First-time buyer subsidies which

[1] Concerns range from central banks to government agencies, think tanks, and banks. See e.g. "Coming of age in the Great Recession", Federal Reserve Board speech by Gov. Brainard, 2015. Housing is the largest asset on households' balance sheets and the main way in which they accumulate wealth (Goetzmann, Spaenjers and Van Nieuwerburgh (2021)), which has motivated numerous policies to stimulate home ownership (Goodman and Mayer (2018)). In 2005, the average home ownership rate of U.S. households was 68.8%. In 2015, it was 62.7% and there were 124.6 million households, that is $(0.688 - 0.627) \times 124.6 = 7.6$ million missing purchases. Even relative to 1995, there were 2.9 million missing purchases in 2015. Source: American Housing Survey.

are identical across regions have little stabilizing effect as they stimulate high-price regions with larger busts by less.

Figure 1: Change in home ownership by age group



Source: American Housing Survey. Values normalized to 100 in 2005. Gray band indicates NBER recession.

I motivate this mechanism by documenting new stylized facts on young buyers using historical time series and a panel of U.S. metropolitan areas for the post-Great Recession period. First, young home ownership after the recession fell deeply and persistently below its long-run average in data going back to 1975 (56.7%), much more than undoing the gains from the boom (47.6% in 2011, 50.2% in 2019). At the aggregate level, this pattern is masked by mean-reversion in total home ownership. Second, the decrease in young home ownership was concentrated in high-price metro areas after 2005. There is a strongly increasing relationship between local house price levels prior to the housing bust and the subsequent drop in young home ownership. Young home ownership fell by 25% in the top 10% of the house price distribution but by only 10% in the bottom 10%. This has led to a persistent increase in the dispersion of home ownership rates between MSAs. Entry into home ownership decreased. Mortgage originations to first-time buyers in high-price MSAs fell by up to 55% compared to 25% in low-price MSAs and they remained low. Households delayed buying by 6 more years on average relative to low-price MSAs, leading to a temporary divergence in the ages of first-time buyers between regions. Third, perhaps surprisingly, these differences were not caused by a larger credit contraction in high-price MSAs. Credit standards, a major determinant of home ownership, changed uniformly nationwide. Loan-to-value (LTV), payment-to-income (PTI), and credit score requirements displayed strong comovements across regions.

I develop an equilibrium spatial macro-finance model consistent with these facts. The economy is subject to local and aggregate shocks to credit standards and income. Regions differ in the amenity benefits that housing provides, construction costs, 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. Two household-level determinants of borrowing constraints differ between cohorts: Millennial income is lower due to the scarring effect of entering the economy in a recession, and their wealth is lower due to student debt. Households consume and save; sort across regions subject to a migration cost; choose to rent or own housing subject to LTV, PTI constraints, and origination fees applying to long-term mortgages; and to repay or default on their mortgages, subject to a finite cost which generates default risk and captures the action of unmodeled credit standards.

The model accounts for three features from which spatial macro-finance models typically abstract: (i) the distribution of house prices and rents responds endogenously to local and aggregate shocks; (ii) households are mobile across regions; (iii) overlapping cohorts differ. This setting allows to disentangle the effects of local and aggregate shocks, while accounting for local price and migration responses.[2] I map the steady state and dynamic responses in the model to the panel of MSAs, and calibrate regional differences and mobility using indirect inference. I then use a series of counterfactual experiments to identify the causes and consequences of the missing home buyers after the recession.[3]

Along the transition path, an *identical* tightening of credit standards across regions (chosen to match the decrease in household leverage after the recession) generates *heterogeneous* housing busts. Local income shocks have little effect. The aggregate credit contraction fully explains the 10% decrease in young home ownership in low-price MSAs and the 20% decrease in high-price MSAs, without targeting them. As in the data, the overall decrease in home ownership is driven by young buyers, and concentrated in high-price MSAs. Changes in Millennial preferences towards owning are not needed to explain this decrease, consistent with survey evidence. The impact of the credit contraction is endogenously more persistent in high-price MSAs. Home ownership and prices remain low four years after the shock as households delay buying.

A decomposition of credit constraints over buyers' life-cycles shows that there are more credit-constrained buyers in high-price MSAs. While most young buyers are constrained by LTV limits, that fraction quickly falls with age while that of PTI-constrained buyers grows and eventually dominates. This result refines popular narratives which focus on Millennials' lack of down payments. PTI constraints are important because fric-

[2]This paper is the first to relax the assumptions of exogenous house prices and no mobility in such models (e.g., Hurst, Keys, Seru and Vavra (2016)), an important research avenue in macro-finance according to the discussion of Guren, McKay, Nakamura and Steinsson (2020).

[3]I develop a solution method to compute the transition dynamics of the price distribution in this class of models, in response to unanticipated local and aggregate shocks.

tions to spatial arbitrage prevent the perfect sorting of poorer buyers into low-price MSAs and richer buyers into high-price ones, a novel mechanism. Households tend to have higher income in high-price MSAs, but sorting by income is limited because of moving costs and the option to rent, which allows households to enjoy better amenities without owning. Thus regional income differences are not high enough to compensate for house price differences.

I study counterfactual transitions to further characterize the period effect of the credit contraction. The impact of regionally-binding constraints is time-varying as higher local prices make first-time buyers more sensitive to changes in credit standards. Under the more equal house price distribution of 1995, the same credit contraction would have generated *similar* busts in young home ownership across MSAs, unable to account for its protracted decline. In contrast, high-price MSAs see much larger busts under the baseline 2005 distribution. House prices fall by 10% and 20% in low- and high-price regions, replicating half of the difference in price changes in the data. I estimate that these differences are explained in equal parts by tighter housing supply restrictions and better amenities in high-price MSAs. Geographic variation in these two factors provides a novel microfoundation for variation in PTI constraints in the population.

At the cohort level, income scarring and student debt make credit constraints more binding and double the drop in Millennial home ownership in the short run. In the long run, they permanently lower average home ownership (-6 pp) and house prices (-6%), most of which is due to income scarring. Their effect is three times larger in high-price MSAs because they induce some credit-constrained buyers to leave and buy in low-price MSAs. In spatial equilibrium, they generate a "migration accelerator" which stimulates low-price owner-occupied markets. They also generate a boom in high-price rental markets as inactive households delay buying and consume more rental housing. These effects are crucial for measuring the total impact of cohort effects on housing markets. They are absent from single-region models and consistent with recent migration data.[4]

I conclude by evaluating how effective subsidies to first-time buyers are at relaxing regionally-binding constraints during the recession. I study the First-Time Homebuyer Credit (FTHC), a tax incentive of $8,000 given uniformly to new buyers in 2009. I use the model to quantify the dynamic impact of the policy on buyers' welfare, an open question for empirical analyses relying on average treatment effects (e.g., Berger, Turner and Zwick (2019)). Along a counterfactual transition path, the FTHC increases young home

[4]An example are households moving from San Francisco to Austin, Denver, Raleigh (e.g., Frey (2019)).

ownership and generates a sizable increase in aggregate welfare equivalent to 1.5% of four years of non-durable consumption. Welfare gains come from four sources: owning allows buyers to live in larger units, enjoy higher amenity benefits, hedge against rent increases, and quickly accumulate wealth when the rate of return on housing increases.

The model highlights two limitations of the policy which dampen its effectiveness. First, the "one size fits all" subsidy relaxes credit constraints more in low-price MSAs with lower average house prices ($100,000) than in high-price MSAs ($240,000). Therefore it cushions half of the home ownership bust in the former but only one seventh in the latter. Since the decrease in home ownership is concentrated in high-price MSAs, the aggregate impact is limited. Second, the estimated amenity benefits imply that all else equal households get more utility from buying in high-price MSAs. While welfare gains in those regions are higher conditional on buying, the FTHC induces fewer renters to buy in high-price than in low-price MSAs, dampening the total welfare effect. Due to these limitations, a budget-neutral *place-based* version of the FTHC where subsidies are proportional to local house prices improves the welfare gain by a third, without increasing the dollar cost of the policy. This result suggests that stabilization policies should target high-price housing markets because they are more volatile in downturns.

Related Literature This paper departs from existing settings by explicitly connecting two separate strands of the literature in a spatial macro-finance framework: dynamic and stochastic models with portfolio choices, which abstract from spatial variations; and empirical analyses using regional panel data for identification, which are silent on general equilibrium and welfare effects.[5] Quantitative implications arise which refine and sometimes challenge existing narratives of housing busts: different local changes in housing markets are less due to different local shocks than to different responses to the same aggregate shock; the resulting decrease in young home ownership is much deeper than mean-reversion from the boom and it is not due to lower Millennial preferences for owning; some migration away from high-price regions did amplify their busts but it also dampened them in low-price regions; unlike most place-based policies, housing stabilization policies which target high-price regions with higher income are more effective.

My work contributes to the literature on regional heterogeneity and financial shocks.

[5] Examples of portfolio choice models with housing include Cocco (2005), Favilukis, Ludvigson and Van Nieuwerburgh (2017), Chen, Michaux and Roussanov (2020), Kaplan, Mitman and Violante (2020). Examples of identification using regional variations include Mian and Sufi (2009), Mian, Rao and Sufi (2013), Mian and Sufi (2014), Stroebel and Vavra (2019). Ortalo-Magné and Prat (2015) study a stylized spatial asset pricing model.

I decompose the impacts of local and aggregate shocks, which existing work suggests are very different (e.g., Nakamura and Steinsson (2014)). I find that aggregate mortgage quantity limits are a key determinant of local housing dynamics, similar to risk-adjusted mortgage rates equalized across regions in Hurst et al. (2016). My findings on regionally-binding constraints relate to Beraja, Fuster, Hurst and Vavra (2019), who find that more heterogeneous house price distributions lower the impact of monetary policy on refinancing. I depart from these papers by endogenizing the regional distribution of house prices and allowing for household mobility subject to migration frictions. Limits to spatial arbitrage make high-price regions more sensitive to a tightening of credit standards, in contrast with frictionless models where buyers can move away from borrowing constraints. House prices respond more to shocks if local borrowing constraints are more binding as documented empirically by Lamont and Stein (1999).

I share my emphasis on mortgage standards with Favilukis et al. (2017), Greenwald (2018), and Justiniano, Primiceri and Tambalotti (2019). In addition to their analyses of the time series, I consider geographic variation in those constraints and how they are microfounded by local housing characteristics. I show that a local market needs not have a stronger PTI tightening to have a larger response, as in Johnson (2020), but that it can also be more elastic to the same tightening. Landvoigt, Piazzesi and Schneider (2015) and Carozzi (2020) find that buyers' assignment into housing market segments *within* a region leads cheaper homes to have more volatile prices. I show that this response depends on the level of aggregation considered. In my setting, households sort *between* regions, which leads high-price regions to be more volatile, not less. Together, these findings imply that real-world subsidies should target low-price homes within high-price MSAs.[6]

My analysis focuses on the post-Great Recession period as Guren and McQuade (2020) and Piskorski and Seru (forthcoming). These papers focus on exit from home ownership through foreclosures. By studying entry rates, my paper complements the rich literature focusing on mortgage default (e.g., Campbell and Cocco (2015), Guren, Krishnamurthy and McQuade (2021)). Instead of policies focused on exit rates, I study first-time buyer subsidies as Berger et al. (2019). I use the model to quantify their welfare effect and how they are affected by regional heterogeneity, a challenge for empirical analyses. My results on higher subsidies in high-price MSAs contribute to the nascent literature on place-based mortgage policy (e.g., Han, Lutz, Sand and Stacey (2021)).

Finally, I contribute to the literature on young home buyers, whose importance was

[6] Favilukis, Mabille and Van Nieuwerburgh (2021) study related housing affordability policies in a spatial model, but they focus on a single MSA and a steady state without local and aggregate shocks.

first emphasized by Mankiw and Weil (1989) for the Baby Boom cohort and then by Ortalo-Magné and Rady (2006). My approach complements a growing empirical literature (Goodman and Mayer (2018)) which separately studies the causes of the decrease in Millennial home ownership. Instead, I jointly estimate the contribution of several popular explanations in a structural model. Those include borrowing constraints (Acolin, Bricker, Calem and Wachter (2016)), income scarring, and student debt (Bleemer, Brown, Lee, Strair and van der Klaauw (2021), Isen, Goodman and Yannelis (forthcoming)).[7]

Outline The rest of the paper is organized as follows. Section 2 documents stylized facts on young buyers. Section 3 presents the spatial macro-finance model. Section 4 describes the calibration which links the model to the panel of MSAs from Section 2. Sections 5 and 6 decompose period and cohort effects by analyzing the response of housing markets to a recession with regionally-binding constraints and their household-level determinants. Section 7 studies implications for stimulus policies, and Section 8 concludes.

2 Evidence on Young Home Buyers

This section documents stylized facts on young buyers and provides motivating evidence on the role of regional heterogeneity. There is little evidence on young buyers' access to credit and home ownership. One reason is that the distinction between borrower-level and loan-level datasets does not allow to identify the characteristics of loans taken by borrowers at various ages. To circumvent this limitation, I exploit data on first-time buyers, which are identified in both types of datasets.

2.1 Data Description

I assemble a regional panel dataset, in which I merge borrower-level and loan-level information on first-time buyers at the MSA level. In the next sections I use this panel to calibrate the steady state and dynamic responses in the model. First-time buyers account for almost 50% of purchase mortgages originations, thus they are quantitatively important for housing markets (Consumer Credit Panel, Federal Reserve Bank of New York).

The panel tracks first-time mortgages in U.S. metro areas at annual frequency since the Great Recession, from 2005 to 2017, the longest sample for which the data is available. I

[7]In recent work, Garriga, Gete and Hedlund (2020) and Ma and Zubairy (2021) study borrowing constraints while abstracting from regional heterogeneity and cohort effects.

merge information on mortgages, household demographics, and house prices at the MSA level, a close equivalent to a local labor market. Weighted averages are computed using local population sizes or loan sizes as weights. Nominal variables are expressed in 1999 dollars using the Bureau of Labor Statistics chained Consumer Price Index for all urban consumers.

To compute long-run time, aggregate series for home ownership by age which go back to 1975, I extend the panel with data at the national level from the American Housing Survey.

Mortgage originations Data on first-time purchase mortgages comes from the Consumer Credit Panel (CCP) of the Federal Reserve Bank of New York. The CCP is a borrower-level, 5% random sample of the U.S. population with credit files derived from Equifax. I use information on the number and balances of mortgages originated by age and for all households, aggregated at the MSA level. The data has information on 370 of the 384 MSAs in the U.S. 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. First-time mortgage originations are large and volatile: 1.417 million loans were originated in 2005, 665,000 in 2011, and 1.059 million in 2017.

Mortgage applications Loan-level information on loan application and acceptance rates comes from the Home Mortgage Disclosure Act (HMDA). HMDA includes information from U.S. financial institutions, including most insured depository institutions and non-bank lenders. In 2017, the last year of my sample, it covered 92% of all originations in the U.S, and its coverage is stable over time. I exclude mortgages which are not for purchase and owner-occupying purposes (e.g., refinance or second home mortgages). Application rates are calculated as the number of applications divided by total MSA population. Denial rates are calculated as the number of applications denied divided by the total number of applications.

Credit standards Information on the characteristics of first-time mortgages comes from the Single Family Loan-Level dataset of Freddie Mac and the Single Family Loan Performance dataset of Fannie Mae. The total stocks of loans are respectively 26.6 and 35 millions. I focus on the flow of new loans, in the loan origination and acquisition datasets. I use the distribution of LTV, DTI ratios, and borrower credit score at origination to measure changes in credit conditions across regions. Government-Sponsored Enterprises (GSE) and Federal Housing Administration (FHA) loans are the primary source of mortgage securitization for first-time buyers since the Great Recession. They represent 50% to 90% of first-time mortgage originations in the CCP data.[8]

Household demographics Demographic data comes from the American Community Survey (ACS) of the U.S. Census Bureau. I use household-level information by MSA on population, age structure, home ownership, migration flows, employment status and median income.

House prices I use the Zillow Home Value Index (ZHVI) and Rental Index (ZRI) for all homes at the MSA level, as measures of median house prices and rents.[9] Since the data is 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 (Rent of Primary Residence in U.S. City Average, All Urban Consumers).

2.2 Classifying Regions

I classify metro areas by the level of local house prices in 2005, and keep this classification fixed throughout the paper. Regions in the bottom percentiles of the house price distribution are referred to as "low-price MSAs" (blue in graphs and tables) and regions in the top percentiles as "high-price MSAs" (red). Economywide aggregates are in black. I then study the evolution of local housing, mortgage, and labor markets within these groups. For most of the analysis, I split the sample into the simplest partition of metro areas: the bottom 50% and the top 50% of the house price distribution. My results do not depend on the date at which regions are sorted.[10]

Appendix Figure 17 plots these groups of regions on a map and Appendix Table 8 lists them. Low-price MSAs are concentrated inside the U.S. (e.g., Detroit MI). High-price

[8] Source: Consumer Financial Protection Bureau (2020). While this dataset from the GSE does not cover the universe of mortgage originations, it is the largest readily available data source. FHA data does not have information on credit standards at origination.

[9] I checked that my results were unchanged with repeat-sale house price indexes, e.g., the All-Transactions House Price Index (U.S. Federal Housing Finance Agency) and the S&P CoreLogic Case-Shiller Home Price Index.

[10] The identities of low-price and high-price metro areas change little over time. For instance, I check that most low- and high-price MSAs in 1997 are still low- and high-price MSAs in 2005.

MSAs are concentrated in coastal regions and the Southwest (e.g., San Francisco-Oakland-Fremont CA).

Dispersion in house price busts between regions Appendix Figure 18 plots house price levels and changes by MSA group. Average house prices are \$100,000 in low-price and \$240,000 in high-price MSAs in 2005 (1999 dollars). They respectively fell by 10% and 45% from 2005 to 2012. High-price MSAs have a 50% larger population than low-price MSAs. Aggregate value- and population-weighted price indexes track high-price MSAs more closely. Households' median and average incomes are 10% and 30% higher in high-price MSAs. Since house prices are more than twice higher, buyers' debt-to-income and payment-to-income ratios are higher in high-price than in low-price MSAs.

2.3 The Missing Home Buyers

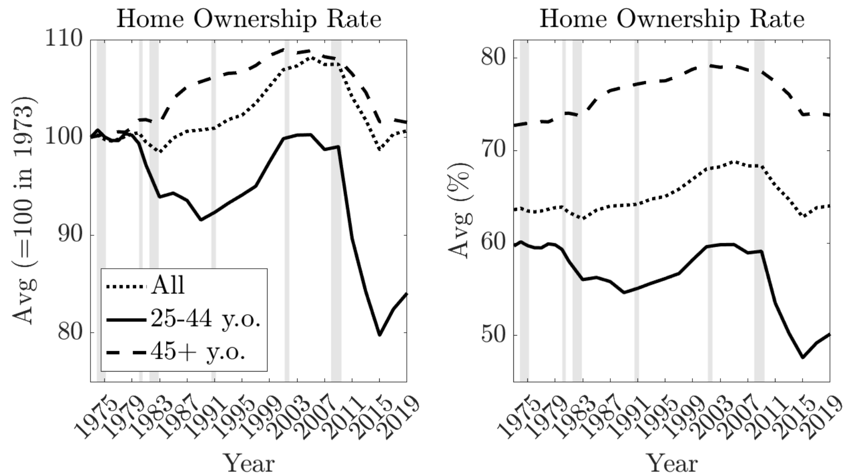
Going back as far as housing data by age allows, Figure 2 shows that the home ownership rate of young households after the recession fell deeply and persistently below its long-run average, much more than undoing the gains from the boom. In the aggregate, this pattern is masked by mean-reversion in the average home ownership rate after the boom, following the popular narrative among economists. This pattern motivates the focus of the rest of the paper on the post-Great Recession period rather than the entire housing cycle. In addition, starting in 2005 allows to keep the model tractable and to link it with the regional panel for which no prior data is available.

Relative to 2005, the probability of being a home owner fell by up to 20% for 25-44 year old households and 7% for 45+ year old households (Figure 1). Relative to 1975, this decrease was nearly identical for 25-44 year old households and slightly lower for 45+ year old households (Figure 2).

Appendix A.4 further decomposes this decrease across ten-year age groups. It shows that while home ownership fell broadly for all households below 65 years old, the probability of being a home owner fell more for younger households, and this relationship is monotonic: it fell by up to 27% for the 25-34, 16% for the 35-44, 10% for the 45-54, 8% for the 55-64%, 5% for the 65-74, and 2% for the 75-84 age groups. It increased by 3% for 85+ households. This relationship holds both relative to 2005 and long-run averages going back to 1975.

For comparison purposes, Appendix A.5 shows that young households are the population group that is associated with the largest decrease in home ownership since 2005,

Figure 2: Home ownership by age group



Notes: Home ownership rate by age group. Left panel: change, values normalized to 100 in 1973. Right panel: level. Population-weighted averages. Gray bands indicate NBER recessions. Sources: AHS.

using a single sort of changes in conditional home ownership rates against traditional predictors of home ownership such as age, income, race, education, and household composition.

2.4 Young Buyers Across Regions

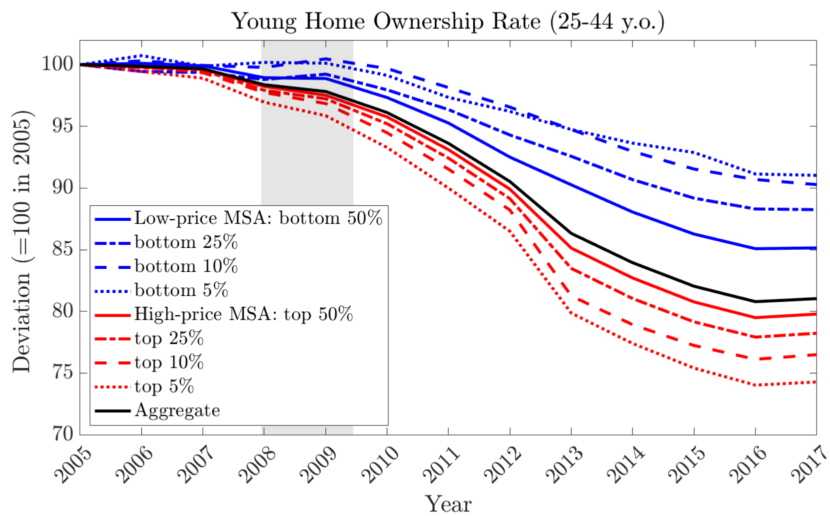
I now document significant regional heterogeneity in young buyers' access to housing. There are large differences between regions in changes in home ownership rates, mortgage originations, first-time buyer ages, and loan application rates.[11]

Young home ownership Figure 3 shows that the decrease in young home ownership is concentrated in high-price metro areas. Regions are sorted by percentiles of the house price distribution. There is a strongly increasing relationship between initial house price levels, and the subsequent drop in young home ownership. Young home ownership fell by more than 25% in the top 10% of the price distribution but by only 10% in the bottom 10%. This relationship has led to a regional divergence in young home ownership rates (Appendix Figure 26). There is no such relationship for older households, for which rates fell equally across regions, by less than 5% (Appendix Figure 22).

After documenting this relationship, I focus on the simplest partition of metro areas in the panel dataset, between the top 50% and the bottom 50% of the house price distri-

[11] Appendix A.7 shows the levels of these variables. The model will target both levels and changes.

Figure 3: Change in young home ownership by region group



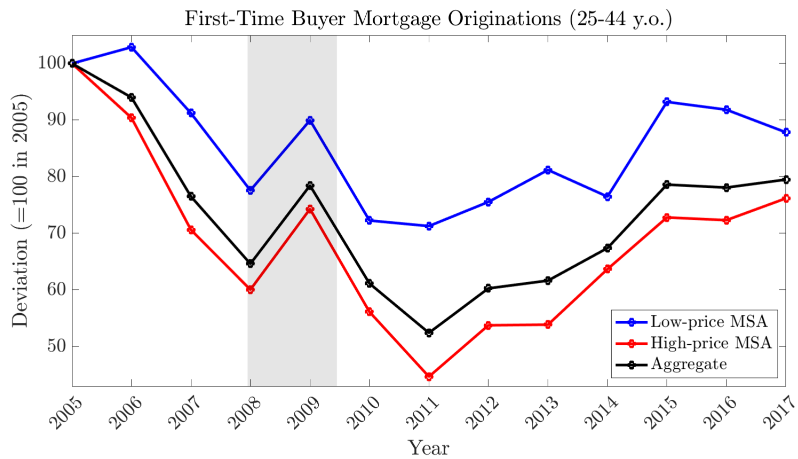
Notes: Changes in 25-44 year old home ownership rate for various groups of MSAs in the house price distribution: bottom and top 50% (solid lines), bottom and top 25% (dashed-dotted lines), bottom and top 10% (dashed lines), bottom and top 5% (dotted lines) in 2005. Blue: bottom of the distribution ("low-price MSA"). Red: top of the distribution ("high-price MSA"). Black: economy average. Population-weighted averages. Values normalized to 100 in 2005. Gray bands indicate NBER recessions. Sources: ACS, Zillow.

bution. This classification provides a lower bound on the changes that I document, and it is the simplest setting to calibrate the model in the next sections.

Mortgage originations Figure 4 shows that the flow of mortgage originations to first-time buyers has decreased more in high-price MSAs (-55%) than in low-price MSAs (-25%) since 2005, consistent with regional heterogeneity in home ownership busts. Originations temporarily increased in both regions in 2008-2009, when the First-Time Home Buyer Credit (FTHC) was implemented to stimulate housing markets. Originations stabilized in low-price MSAs, but they decreased further in high-price MSAs. They have not yet fully recovered in 2017, and remain lower in high-price MSAs (-25%) than in low-price MSAs (-10%). In Section 7, I use the model to explain why the FTHC stabilized low-price regions better than high-price regions, and how its effectiveness could be improved.

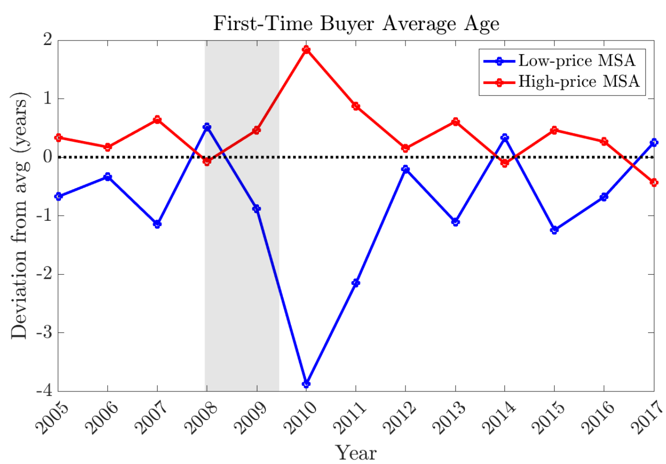
Age of first-time buyers Figure 5 shows that at the beginning of the period, conditional on buying, households in high-price MSAs delayed home ownership over their life-cycles. Relative to 2005, the average age of fist-time buyers increased by 2 years in high-price MSAs (from 40 years old), while it fell by 4 years in low-price MSAs (from 39 years old), at the same time that the First Time Homebuyer Credit was introduced. This led to sixfold increase in their difference in the early 2010s, which then decreases.

Figure 4: Change in first-time mortgage originations by region group



Notes: Changes in the average flows of mortgages originated to first-time buyers in low- (blue) and high-price MSAs (red). Flows are normalized by local 25-44 year old population sizes. Black line: economy average. Values normalized to 100 in 2005. Population-weighted averages. Gray bands indicate NBER recessions. Sources: CCP/Equifax, Zillow.

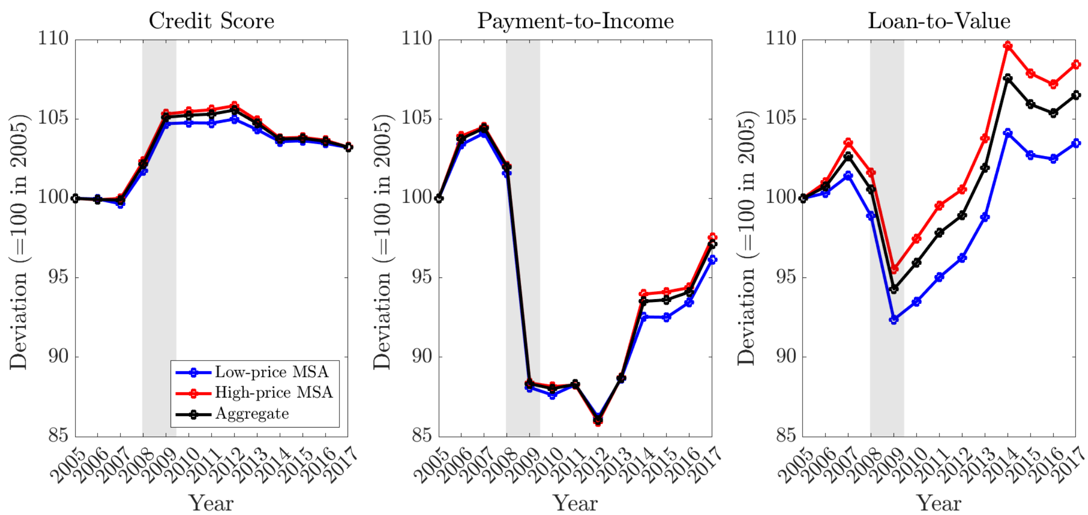
Figure 5: Change in age of first-time home buyers by region group



Notes: For each MSA group, the age of first-time buyers is calculated as a weighted average of the various age groups using the number of loans originated in each age group as weights. Results are similar when using loan values as weights instead. The average age of first-time buyers in the economy is then subtracted from the average regional ages to control for long-run changes. Hence the resulting plotted series are deviations from the economy average. Blue: low-price MSAs. Red: high-price MSAs. Population-weighted averages. Gray bands indicate NBER recessions. Source: CCP/Equifax, Zillow.

Credit standards Mortgage credit largely determines access to home ownership for first-time buyers because they have low income and wealth. Does a larger local credit contraction explain the larger decrease in home ownership, mortgage originations, and loan applications in high-price MSAs? Figure 6 shows that this is not the case. It plots changes in credit conditions by metro area, measured by maximum LTV, PTI ratios, and credit scores at origination. All of them display strong comovements across regions, with credit standards becoming uniformly tighter across metro areas over the period. The tightening of PTI ratios (-15%) is the largest and most persistent. The increase in minimum credit scores (+5%) is also persistent. The tightening of LTV ratios is smaller (-6%) and shorter-lived.[12]

Figure 6: Change in credit conditions by region group



Notes: Left panel: average change in top quartile (P75) of the credit score distribution of first-time buyers at mortgage origination. Middle panel: average change in top quartile (P75) of the payment to income distribution of first-time buyers at mortgage origination. Right panel: average change in top quartile (P75) of the loan to value distribution of first-time buyers at mortgage origination. Blue low-price MSAs. Red: high-price MSAs. Black: economy average. Population-weighted averages. Variables normalized to 100 in 2005. Gray bands indicate NBER recessions. Source: Fannie Mae, Freddie Mac, Zillow.

In contrast, local income contracted by less than credit standards across regions, and it contracted by more in high-price MSAs. Appendix Figure 25 shows that annual total payroll fell on average by 5% in high-price MSAs (0.1% in low-price MSAs), median income by 4% (2%), and the number of employees by 6% (3%).

Mortgage applications Appendix Figure 23 explores the sources of lower originations to first-time buyers. They have largely been driven by a decrease in loan application rates, rather than an increase in rejection rates. The decrease in application rates is persistent, and larger in high-price MSAs, where application rates are 75% lower in 2017 than in

[12] This paper focuses on average credit standards rather than on selection between government-backed and private-label loans as an explanation for the decrease in young home ownership. GSE and FHA loans represent 50% to 90% of first-time mortgage originations in 2000-17 (source: CCP/Equifax), a larger share than private-label loans which justifies my approach as a first step to characterize the credit environment faced by young buyers. Mian and Sufi (forthcoming) also contend that almost all of the variations in transactions in areas relying on private mortgage was driven by speculators and not first-time buyers. Finally, the composition of new mortgages is not a concern for my main quantitative analysis as changes to credit standards in the model are calibrated to replicate the decrease in household leverage in the data.

2005, compared to 40% lower in low-price MSAs. It is quantitatively important, of the same order of magnitude and more persistent that the increase in foreclosure rates during the same period (Appendix Figure 24). Acceptance rates only fell by 10% in 2006-2007.

2.5 Numerical Example

Before turning to the quantitative model, I use a numerical example to illustrate how regionally-binding credit constraints can account for those features of the data. Because it is limited by its simplicity and data availability, it is only meant to convey the intuition based on representative agent logic, which is refined in the model.

Consider a stylized mortgage contract. Denote the mortgage rate as r^b, the loan maturity as n, and LTV and PTI requirements by θ_{LTV} and θ_{PTI}. An annuity formula implies that the maximum loan size due to the PTI constraint is

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

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

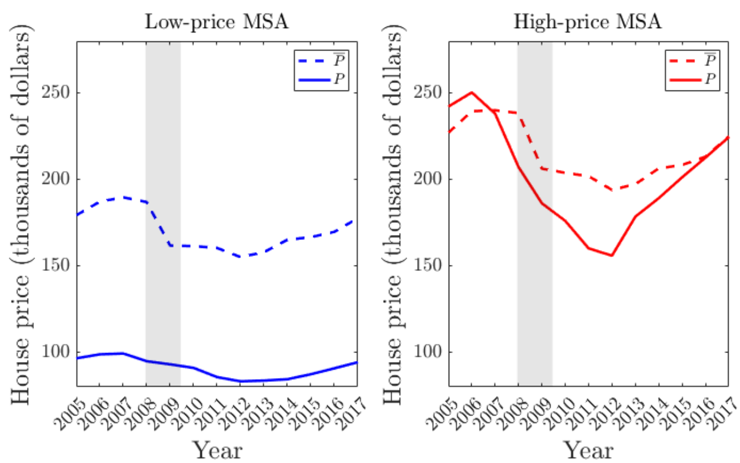
$$\text{max. affordable price } \overline{P} = \min\left[\frac{1-(1+r^b)^{-n}}{r^b}\theta_{PTI} Y + \text{down}, \frac{\text{down}}{1-\theta_{LTV}}\right] \tag{2}$$

Figure 7 plots the maximum affordable price and the actual house price for each set of metro areas, feeding in values for the empirical counterparts of the variables in Equation 2. $n = 30$ years is the average mortgage maturity in the U.S., $r^b = 6.4\%$ is the average annual rate on 30-year fixed rate mortgages at the beginning of the sample (Primary Mortgage Market Survey, Freddie Mac), $\{Y_{j,t}\}$ is a time series of median household income (ACS), $\{\theta_{PTI,j,t}\}$ and $\{\theta_{LTV,j,t}\}$ are time series for PTI and LTV ratios (Single Loan Level Datasets, Fannie Mae and Freddie Mac, 90$^{\text{th}}$ percentiles), down $= \$12,000$ is the median down payment in 2005 (Residential Property Loan Origination Report, ATTOM Data Solutions). Nominal variables are in 1999 dollars. j denotes low- and high-price MSAs.[13]

[13]The annual 30-year fixed mortgage rate trended down from 2005 to 2017, with an average of 4.8% and a minimum of 3.7%. In this example and in the model, I checked that falling rates do not affect my explanations for lower entry into home ownership by Millennials. To match the decrease in household leverage, a lower rate requires a larger tightening in credit standards. For simplicity, it is fixed in the main exercise.

There are three takeaways. First, maximum affordable prices $\overline{P}$ (dashed lines) are higher in high-price regions than in low-price regions, because average household income and wealth are higher. Second, actual median house prices P (solid lines) are much closer to $\overline{P}$ in high-price regions, suggesting that credit constraints are more binding. In contrast, P is well below $\overline{P}$ in low-price regions, where constraints are slack. Third, there is a strong covariance between P and $\overline{P}$, especially in high-price regions where constraints are binding. Changes in equilibrium prices are associated with changes in credit standards and local income. Lastly, changes in the maximum affordable price $\overline{P}$ are due to the PTI limit rather than to the LTV limit in all years, except 2008 in high-price regions. I these calculations, constraints bind ($P \geq \overline{P}$) because of the PTI limit for 5 years out of 6.

Figure 7: Regional credit constraints: numerical example



Notes: Left panel: actual price P (solid line) and maximum affordable price $\overline{P}$ (dashed line) in low-price MSAs (blue). Right panel: actual price P (solid line) and maximum affordable price $\overline{P}$ (dashed line) in high-price MSAs (red). $\overline{P}$ is calculated using Equation 2 and time series from the data described in the main text. Gray bands indicate NBER recessions. House prices are in 1999 dollars.

The rest of the paper develops a quantitative model which addresses several resulting questions: What is the role of heterogeneity in household income and wealth? Do the options to rent and to migrate between regions alleviate credit constraints? What is the effect of local versus aggregate shocks?

3 Spatial Macro-Finance Model

This section describes an equilibrium model of the cross-section of housing markets with heterogeneous agents and incomplete markets. The model has three features: (i) The dynamics of the regional distribution of house prices and rents is endogenous and responds to local and aggregate shocks. (ii) Households are mobile across regions. (iii) Overlapping cohorts have different initial states. Solving such a model is numerically challenging. I develop a tractable solution method to calibrate this class of models and solve for the transition dynamics in response to unanticipated shocks.

3.1 Environment

The economy consists of two building blocks. First, two sets of regions corresponding to low-price and high-price metro areas in the data ($j = L, H$) are connected by migrations. Regions differ in their amenity benefits from housing, construction cost, price elasticities of housing supply, exposures to aggregate income shocks. Second, each set of regions consists of an economy with heterogeneous agents and incomplete markets. Each 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. Households have rational expectations. 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 Ξ. A household's instantaneous utility function in region j is

$$\frac{u\left(c_t, h_t\right)^{1-\gamma}}{1-\gamma} + \Xi_j^{\mathcal{H}} \equiv \frac{\left[\left((1-\alpha)c_t^{\epsilon} + \alpha h_t^{\epsilon}\right)^{\frac{1}{\epsilon}}\right]^{1-\gamma}}{1-\gamma} + \Xi_j^{\mathcal{H}} \tag{3}$$

The taste shifter $\Xi_j^{\mathcal{H}}$ depends on region $j = L, H$ and on home ownership status $\mathcal{H} = o, r$. It captures the amenity benefits accruing with different locations and with owning. Renters in region j enjoy benefits $\Xi_j^r = \xi_j^r$, with the normalization $\xi_L^r = 0$. Homeowners enjoy higher benefits $\Xi_j^o = \xi_j^r + \xi_j^o$. They only own one home in a single size, which delivers a fixed flow of services $\overline{h}$. Renters consume continuous quantities of housing services $h_t \in \left(0, \overline{h}\right]$.

Bequests are accidental and not chosen by households. They are a normal good and are redistributed equally. They are captured by a warm-glow motive:

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

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 the deterministic life-cycle income profile. $e_{i,t}$ is the logarithm of the persistent idiosyncratic component of income for household i. $\eta_{US,t}$ is the aggregate component of regional income shocks, which are zero in steady state. β_j is the sensitivity of income in region j to aggregate income $\eta_{US,t}$.[14]

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 stochastic components of individual income. It creates a motive for higher income households to live in regions with higher average income (if $\eta_{US,t} \neq 0$).

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

Inactive renters who do not buy a home 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 pay off their mortgages first.[15]

To account for the exit margin from home ownership, mortgages are defaultable and non-recourse. Upon default, houses used as collateral return to the market as part of supply. Defaulters incur a utility penalty d, are forced to rent in the same region, and can

[14] The assumption of identical processes across regions for $e_{i,t}$ can be easily relaxed.

[15] The assumption that indebted owners cannot save accounts for the large fraction of "wealthy hand-to-mouth" households with little liquid assets in the data (Kaplan and Violante (2014)).

buy a new home with probability 1 in the next period, which corresponds to four years. Owners cannot refinance and extract housing equity.[16]

Cohort differences All households enter the economy as renters. They are divided into two types, Millennials and non-Millennials. Non-Millennials enter the economy prior to 2005, they draw a level of initial wealth equal to the average bequest, and their initial income from the stationary distribution. Millennials enter after 2005 and have two distinct features. First, their wealth is lower by a fixed amount corresponding to student debt payments in the first periods of their lives (from their twenties to their early thirties). Second, they have persistently lower incomes due to the scarring effect of entering the labor market during a recession. They draw their initial income from a distribution that is first-order stochastically dominated by the distribution for non-Millennials.

Taxes and transfers Labor income is subject to a progressive tax and transfer schedule (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 replicates the main features of the U.S. pension system (Guvenen and Smith (2014), see Appendix Section B.1).

Household choices Every period, households choose to either rent or own. The rental and owner-occupied housing markets 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 size can be chosen continuously in $\left(0, \overline{h}\right]$ at rent R_j. Households choose whether to move between metro areas. If they do, they incur additive fixed moving costs m in terms of utility. Finally, they choose nondurable consumption c_t, and save in a one-period risk-free bonds or borrow with a long-term mortgage b_t. They inelastically supply one unit of labor to the local labor market.

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

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

[16]This assumptions can be relaxed, but it is not crucial for the dynamics of home ownership.

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 supplies housing according to a reduced-form upward-sloping schedule,

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

The construction cost $1/\overline{I}_j$ and the price elasticity of housing supply ρ_j differ between regions. The lower $\overline{I_j}$, the higher the price level required to induce a given level of residential investment. The lower ρ_j, the larger the price movements required to induce a given change in residential investment in percentage terms.

Markets for owner-occupied housing and for rentals are segmented. The housing stock $H_{t,j}$ (in square feet) is divided into a fraction ho_j^{sqft} of owner-occupied units and a fraction $1 - ho_j^{sqft}$ of rentals. This assumption keeps the model tractable and approximates empirical estimates which imply close to full segmentation (Greenwald and Guren (2020)). The supply of owner-occupied houses and of rentals are respectively equal to

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

With positive default rates, housing supply is higher by an amount equal to the measure of foreclosed houses going back to the market multiplied by their square footage.

Timing A household in a given region makes discrete home ownership and location choices, then earns labor and financial income in its region of origin, makes consumption, savings or debt, and housing choices.

3.2 Household Problem

This section describes the household problem in recursive form. The individual state variables are its tenure status $\mathcal{H} = r, o$ (renter or owner), location $j = L, H$ (low-price or high-price region), age a, assets or debt b, and endowment y. I only describe the renter and the owner problems for low-price regions L, since the problem is similar for high-price regions H.

3.2.1 Renter

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

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

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

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

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

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

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

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

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

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 financial wealth, $U_{t+1} = \frac{\psi b_{t+1}^{1-\gamma}}{1-\gamma}$.

Mobile renter 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:

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

Home buyer When buying a house in the same region, the renter's value function is

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

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

$$c_t + R_{L,t}h_t + F_m + P_{L,t}\overline{h}(1+f_m) + b_{t+1} = y_t - T\left(y_t\right) + (1+r)b_t, \quad h_t \in \left(0,\overline{h}\right], \tag{17}$$

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,

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

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.

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

Mobile home buyer The value of moving to region H and buying a house is similar, with the addition of the moving cost m:

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

subject to the budget and borrowing constraints

$$\begin{aligned} &c_t + R_{L,t}h_t + F_m + P_{H,t}\bar{h}(1+f_m) + b_{t+1} = y_t - T\left(y_t\right) + (1+r)b_t, \quad h_t \in \left(0,\bar{h}\right], \\ &b_{t+1} \geq -\theta_{LTV,t}P_{H,t}\bar{h} \quad \text{and} \quad b_{t+1} \geq -\frac{\theta_{PTI,t}}{\left(1+r^b-\tilde{\theta}\right)}y_t. \end{aligned} \tag{21}$$

3.2.2 Home Owner

The home owner problem is analogous and described in Appendix B.2. In addition to the options of paying down their mortgages, selling, and moving, owners can also default. Denote the date t value function of an owner starting the period in region L, as $V^{oL}(a,b_t,y_t)$. $d_t^{oL} \in \{oL, oH, rL, rH, d\}$ denotes the associated policy function for the discrete choice problem.

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

Defaulting owner A defaulter does not repay its mortgage, incurs a utility penalty d and becomes a renter in the same region in the next period:

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

subject to the budget and no-borrowing constraints

$$\begin{aligned} &c_t + b_{t+1} = y_t - T\left(y_t\right), \\ &b_{t+1} \geq 0 \end{aligned} \tag{24}$$

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

3.3 Equilibrium

This section defines a dynamic spatial recursive competitive equilibrium, which describes how the economy in steady state responds to unanticipated local and aggregate shocks.

Definition Given exogenous time paths for aggregate shocks to income and credit standards $\{\eta_{US,t}, \theta_{LTV,t}, \theta_{PTI,t}\}$, an equilibrium consists of the following, for region $j = L, H$ and home ownership $\mathcal{H} = r, o$:

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

(ii) value functions $\left\{V_t^{j\mathcal{H}}, V_t^{j'\mathcal{H}'}\right\}$,

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

(iv) a law of motion for the cross-sectional distribution of households $\lambda_t\left(j,\mathcal{H},a,b,y\right)$ 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 (below).

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

$$\int_{\Omega_t^{oj}} \overline{h} d\lambda_t = \underbrace{pop_{j,t} \times ho_{j,t}^{hh} \times \overline{h}}_{\text{owner-occupied housing demand in } j} = \underbrace{ho_j^{sqft} \times H_{j,t}}_{\text{owner-occupied housing supply in } j} \tag{25}$$

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

$$\underbrace{\int_{\Omega_t^{rj}} h_{j,t} d\lambda_t}_{\text{rental demand in } j} = \underbrace{\left(1 - ho_j^{sqft}\right) \times H_{j,t}}_{\text{rental supply in } j} \tag{26}$$

$pop_{j,t} = pop_j(\mathbf{P_t}, \mathbf{R_t})$ denotes the population share of region j at date t and $ho_{j,t}^{hh} = ho_j^{hh}(\mathbf{P_t}, \mathbf{R_t})$ the home ownership rate. $\Omega_t^{oj} = \Omega^{oj}(\mathbf{P_t}, \mathbf{R_t})$ 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. These objects depend on the vectors of prices and rents in both sets of regions because of spatial sorting.

Solution Appendix B.4 describes the numerical solution of the model, which exploits the homogeneity of the housing supply function in P_j.

4 Calibration and Baseline Results

This section describes how the spatial macro-finance model of Section 3 is calibrated and linked to the regional panel dataset from Section 2. The model replicates central features of housing and labor markets in the aggregate and in the cross-section of metro areas.

4.1 Calibration

Table 1 summarizes the calibration. Parameters are first split into externally and internally calibrated parameters, and then into aggregate and regional parameters. As in the data, metro areas are split into two groups. Since house prices are determined in equilibrium, structural parameters are chosen to endogenously generate the same low-price regions ("Region L") and high-price regions ("Region H") as in the data. A period in the model represents 4 years, and the reference year is 2005. Average worker income Y is normalized to 1.

4.1.1 External Parameters

Aggregate parameters These parameters are common to the two sets of regions.

Preferences. The utility function is CRRA with $\gamma = 2$, a standard value which I further discuss it below. The CES aggregator u has an elasticity of substitution between nondurable consumption and housing of 1.25 (Piazzesi, Schneider and Tuzel (2007)).

Labor income process. The persistence is 0.6867, and the standard deviation is 0.3868. Those values are implied by the annual estimates of Floden and Lindé (2001).

Housing depreciation. I restrict the depreciation rate δ to be the same across regions for simplicity. It is equal to 2.39% per year, 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 $r^b = 0.050$, the average 30-Year Fixed Rate Mortgage Rate in the U.S. prior to the 2000s housing cycle (Freddie Mac, Primary Mortgage Market Survey) minus the CPI inflation (BLS).

The amortization rate $\widetilde{\theta}$ 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 (forthcoming).

The proportional transaction cost of selling a house is $f_s = 0.060$, a standard value. The fixed and proportional mortgage origination fees are $F_m = \$1,200$ and $f_m = 0.8\%$ (Freddie Mac, Primary Mortgage Market Survey).

Student debt. Student debt is modeled as a negative lump-sum transfer which lowers the initial wealth of households entering the economy after 2005 in the first periods of their lives. Its amount depends on age and income according to a realistic schedule constructed using data from the Survey of Consumer Finances and the U.S. Department of Education (Appendix B.1). At the end of the sample, more than 60% of graduating households have student debt, whose average level is close to $40,000.

Income scarring. I use empirical estimates for the effect on lifetime earnings of entering the labor market during a recession to calibrate the initial income distribution $\{e_0\}$ from which Millennials draw. 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. 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 if they had graduated in normal times. I choose the average of the distribution of $\{e_0\}$, $\mu_{e_0} = -0.20$ to match that moment when simulating a panel of Millennial households.

Table 1: Calibration

Parameter	Explanation	Value	Source/Target
External: aggregate			
γ	Risk aversion	2.000	See text
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)
$\underline{Y}$	Min. income	0.100	Guvenen and Smith (2014)
b_0	Student debt	see text	SCF, U.S. Department of Education
$F_{y_0}(.)$	Millennial initial income distribution	see text	Based on Kahn (2010)
r^b	Mortgage rate	0.050	30-year fixed rate mortgage rate
$\tilde{\theta}$	Mortgage duration	0.969	Greenwald et al. (forthcoming)
f_s	Transaction cost selling	0.060	See text
F_m	Fixed mortgage origination fee	0.006	Freddie Mac
f_m	Proportional mortgage origination fee	0.008	Freddie Mac
δ	Housing depreciation/maintenance	0.015	BEA
External: regional			
ρ_L, ρ_H	Housing supply elasticity	2.700,1.800	Saiz (2010)
ho_L^{sqft}, ho_H^{sqft}	Fraction owner-occupied sqft	0.840, 0.860	Homeownership sqft (AHS)
β_L, β_H	Sensitivity to agg. income	0.27, 1.15	Estimates (CBP)
Internal: aggregate			
β	Discount factor	0.952	Wealth/income=4.4 (bottom 80%)
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
d	Utility cost of default	0.75	Avg default rate=0.5%
m	Utility cost of moving	2.750	Avg moving rate L-H=1.7%
τ	HSV tax/transfer progressivity	0.290	Avg marginal 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	$P_L = \$100,000, P_H = \$240,000$
Ξ_L^r, Ξ_H^r	Amenity benefits	0.000,0.508	$R_L = \$1,111, R_H = \$1,206$
Ξ_L^o, Ξ_H^o	Additional home ownership benefits	0.822,0.904	$ho_L^{hh} = 69\%, ho_H^{hh} = 67\%$

Notes: One model period is four years. Parameters and targets are annualized. Sources are as follows. The 30-year fixed rate mortgage rate is from Freddie Mac's Primary Mortgage Survey. The wealth/income ratio is for the bottom 80% of households in the SCF. 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). The average default rate in 2007 from RealtyTrac. The tax rate targets are from Heathcote et al. (2017). The bequest targets are from the SCF. House prices and rents (monthly) are from Zillow (in 1999 dollars), homeownership rates are from the ACS, the average rent/average income ratio is from the CEX (includes utilities). Amenity benefits in Region L are normalized to zero.

Regional parameters These parameters differ between regions.

Regional business cycle sensitivity. High-price regions have a higher sensitivity than low-price regions to aggregate income shocks, $\beta_H = 1.75 > \beta_L = 0.27$. To obtain these values, I estimate the elasticity of median income to U.S. income at the MSA level, using a panel of MSAs in County Business Patterns. Estimates are then matched with the main dataset, and averaged by region groups using population sizes as weights.[17]

Housing supply elasticity. Using the same procedure, I merge estimates from Saiz (2010) and average them using population sizes as weights. I obtain $\rho_L = 2.7$ and $\rho_H = 1.8$.

Owned square footage. The fraction of square footage devoted to owner-occupied units is similar in the two sets of regions, around 80% (AHS). This number reflects, first, that home ownership rates among households are similar across regions and close to the aggregate rate of 68.8%; second, that owner-occupied units are on average 50% larger than rentals (Chatterjee and Eyigungor (2015)).

4.1.2 Internal Parameters

Aggregate moments The following parameters are chosen to match aggregate moments.

Discount factor. β is chosen to match a ratio of aggregate wealth to aggregate income of 4.4 for the bottom 80% of households (Survey of Consumer Finances).[18]

Housing services. The CES weight α on housing services is chosen to match an average rent to average income ratio of 0.20 as measured in the Consumer Expenditure Survey (including utilities).

Mortgage spread. $\iota = r^b - r = 0.6\%$ 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 a ratio of 0.37 for 2005. ι implies a value for the rate of return on savings of $r = 0.044$. This value can be viewed as the rate of return on a bundle of liquid assets, which include both low return bonds and high return stocks, a common interpretation.

Credit standards. The maximum loan to value and payment to income ratios $\theta_{LTV} = 0.900$ and $\theta_{PTI} = 0.580$ are chosen to match the 90th percentiles of the LTV and PTI distributions among mortgagors (Greenwald (2018), Kaplan et al. (2020)).

[17] These estimates incorporate the feedback from local house prices into labor income (Mian et al. (2013), Mian and Sufi (2014)).

[18] There is no mechanism in the model to generate high wealth inequality at the top (e.g., heterogeneity in discount factors, "superstar" income levels). For all households, the wealth/income ratio is 5.6.

Mortgage default. The default cost $d = 0.75$ is chosen to match the average foreclosure rate of 0.5% in the cross-section of MSAs in 2005 (RealtyTrac).

Taxes and transfers. I calibrate τ and φ in the schedule $T(Y) = Y - \varphi Y^{1-\tau}$, to match the progressivity and the level of the U.S. tax system (Y is pre-tax earnings). The income-weighted marginal tax rate is 0.33. Net taxes are used to finance wasteful government expenditures. This delivers $\tau = 0.29$, close to empirical estimates (Heathcote et al. (2017)), and $\varphi = 0.90$. The government also imposes a minimum income level equal to 10% of average income, which ensures that households' choice sets are nonempty (Guvenen and Smith (2014)).

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

Regional moments The remaining parameters are calibrated to match regional moments, which determine the sensitivity of local markets to aggregate shocks.

Housing markets. Amenity benefits $\left\{\Xi_j^r\right\}$, supply constraints $\left\{\bar{I}_j\right\}$, and home ownership benefits $\left\{\Xi_j^o\right\}$ in regions $j = L, H$ (three sets of two parameters) are jointly calibrated to match the levels of average rents $\left\{R_j\right\}$, house prices $\left\{P_j\right\}$, and home ownership rates $\left\{ho_j^{hh}\right\}$ (three sets of two moments). I find the following:

(i) Amenity benefits are higher in Region H than in Region L, as implied by higher rents. They represent a utility gain equivalent to 35.6% of the average utility that a household derives from nondurable consumption and housing services in one period (four years). This is consistent with evidence on the strong appeal of high-price metro areas in the 2000s (e.g., Guerrieri, Hartley and Hurst (2013)). These differences create an incentive for households to locate in high-amenity regions, which results in higher local rents and prices through endogenous sorting of buyers by age, income, and wealth.

(ii) 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.[19] This is consistent with those regions having tighter geographic and population constraints in the data (e.g., Mayer (2011)).

(iii) The utility benefits from home ownership are sizable. They represent 63.4% of the average utility that a household derives from consumption in one period. They are slightly higher in Region H, because regional differences in price-to-rent ratio are larger than differences in income (both are higher in Region H). Therefore higher benefits in

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

Region H are required to match similar home ownership rates across regions.

Migrations. Using ACS data on migrations between all pairs of metro areas, I calculate an annual gross migration rate of 1.6% between low- and high-price regions.[20] The model matches that value. The implied utility cost of migrating $m = 2.750$ is equivalent to 280.7% of the average utility that a household derives from nondurable consumption and housing services in a period. This high value is consistent with current estimates of migration costs (Kennan and Walker (2011)), and stands for migration-reducing forces not explicitly modeled. Since m is a fixed additive utility cost, it is larger in welfare terms for older households. Hence it generates a downward-sloping life-cycle profile of migrations as in the data.[21]

4.2 Steady State Results

The model replicates key moments of housing and mortgage markets at the aggregate, household, and regional levels. Aggregate moments are summarized in Table 2. They are obtained by aggregating household-level variables using the cross-sectional distribution of households' locations, home ownership statuses, ages, income, and wealth in 2005.

Table 2: Aggregate moments

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

Notes: Moments targeted by the calibration. Sources (see main text): ACS, SCF, CEX, Flow of Funds. Migration rate annualized.

Table 3 shows that the model also matches the distribution of LTV and PTI ratios, which is not targeted. In addition, it generates close to the right fraction of home owners with a mortgage (66%), and slightly overstates the average size of owner-occupied units relative to rentals (Appendix Table 12).

[20] 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.

[21] m is substantially higher than the default cost d. This is because default is costly even without its utility

Table 3: Aggregate LTV and PTI distributions

	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

Notes: Moments not targeted by the calibration. Sources: Greenwald (2018), Kaplan et al. (2020).

The model generates significant heterogeneity between MSAs. Table 4 shows that it exactly matches the cross-section of house prices levels by virtue of the solution method, and closely matches rents and home ownership rates. Income, which is not targeted by the calibration, is on average 30% higher in Region H than in Region L as in the data, because of endogenous sorting. Importantly, income in Region H is not high enough to fully compensate for house prices, a sign that sorting is limited. Therefore, the resulting price-to-income ratio is higher in high-price regions. The price-to-rent ratio and the population share of high-price regions are also higher.

Table 4: Regional moments

Variable	Data L	Model L	Data H	Model H
Price per unit	100,000	100,000	240,000	240,000
Rent per unit	1,111	1,010	1,206	1,415
Homeownership rate	0.69	0.69	0.67	0.67
Income	29,300	29,309	38,261	38,253
Price/income	3.41	3.41	6.27	6.27
Price/rent	7.50	8.25	16.58	14.13
Population share	0.42	0.39	0.58	0.61

Notes: Top panel: moments targeted by the calibration. Bottom panel: moments not targeted. Sources: ACS, Zillow, BLS. Prices and rents (monthly) in 1999 dollars.

The regional life-cycle profiles of income and wealth (Appendix Figure 32) show that average household wealth is always higher in Region H, except for the youngest households (less than 28 years old). This is first due to higher savings (before age 40), then to higher housing wealth (after age 40). Households in Region H accumulate more savings

cost, as households lose the value of their houses and the benefits of home ownership.

than in Region L because they are more productive and have to meet larger down payment requirements when buying. In contrast, average income is similar across regions for young households (before age 40). This implies higher price-to-income and payment-to-income ratios in Region H, where average house prices are more than twice higher than in Region L. Therefore, young households' decision to buy is more elastic to PTI constraints in Region H.

The model also generates realistic life-cycle profiles of household mobility between regions (Appendix Figure 33). As in the data, younger households migrate more.[22] Among young households, more productive ones migrate more. In the data, unconditional migration rates between metros are slightly decreasing with income, but conditional rates are increasing for young households, especially college-educated ones with higher permanent income.[23] 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 moving.[24]

4.3 Main Features

Two features of the model are crucial for housing markets' responses to shocks.

Risk aversion Long-term mortgages, which must be amortized every period, create a consumption commitment (e.g., Chetty, Sandor and Szeidl (2017)). Households are more reluctant to make this commitment when risk aversion is high and income is low, since it makes consumption smoothing harder. Therefore, risk aversion γ amplifies the decrease in home ownership and prices in response to a negative shock as households are less willing to hold owner-occupied units. More importantly, risk aversion interacts with location choices. Unlike when they are risk-neutral, low-income households are less willing to locate and buy in Region H, which generates spatial sorting by income. This is because the concavity of the utility function makes it more costly for them to sacrifice non-durable consumption to afford higher house prices, and because the consumption commitment

[22] In the ACS, I calculate 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%). Source: 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.

[23] Source: ACS, Table 22. See also Frey (2019), and for anecdotal evidence, "Migrant Millennials are redrawing the map of America", *Financial Times*, 6/26/2018.

[24] During the transition dynamics, 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 (Gopalan, Hamilton, Kalda and Sovich (2020)).

becomes stronger with higher prices. Both effects are absent from traditional urban economics models with risk-neutral households. They are partly alleviated by the options to migrate and to default. When risk aversion is lower, owners migrate and default more often.

Frictions to spatial arbitrage Households can move between regions in steady state and in response to shocks. In steady state, amenity differences and housing costs are the only motive for moving. Households can move if they experience age-deterministic and stochastic income changes that make it too costly to stay in a given region. In response to shocks, households can move to regions where income decreases less and where housing becomes cheaper. Spatial sorting is limited by the fixed moving cost m and the option to rent, which allows households to enjoy higher amenities $\Xi^r_H > \Xi^r_L$ without owning.[25]

5 Time Period Effect

This section presents the main quantitative findings on the regional transmission of aggregate shocks to young buyers and housing markets. I first study the dynamics of home ownership, house prices, and rents. Then I decompose the contributions of income and credit shocks, and analyze the role of heterogeneity in local house prices. I find that regionally-binding credit constraints have shaped the dynamics of young home ownership and housing markets in the post-Great Recession period.

These results are obtained by solving for the nonlinear transition dynamics of the two-region economy in response to unanticipated aggregate shocks to income and mortgage standards, $\{\eta_{US,t}\}$ and $\{\theta_{LTV,t}, \theta_{PTI,t}, F_{m,t}, f_{m,t}\}$. It involves solving for the full paths of four prices $\{P_{L,t}, P_{H,t}, R_{L,t}, R_{H,t}\}$.

5.1 Heterogeneous Housing Market Dynamics

Aggregate Shocks The recession consists of a sequence of negative shocks to income and credit standards, which enter as inputs into the model. One period is four years. The first period is 2002-05 ($t = 0$), prior to the bust. The aggregate income shock $\{\eta_{US,t}\}$ in 2006-09 and 2010-13 ($t = 1, 2$) is chosen to generate the same decrease in real average income of 9.2% and 1.8% as in the data, relative to 2005. Because $\beta_H > \beta_L$, it translates

[25] It is straightforward to add exogenous moving shocks, but not needed because the calibrated model endogenously generates realistic migration patterns between metro areas.

into a larger shock in high-price regions as in the data. Average income falls by up to 2% in low-price metro areas and 11% in high-price metro areas.

The maximum LTV and PTI constraints $\{\theta_{LTV,t}, \theta_{PTI,t}\}$ in 2006-09, 2010-13, and 2014-2017 ($t = 1, 2, 3$) are chosen to generate a 20% decrease in leverage from 2005 to 2014 as in the data. The decrease in the maximum LTV is exogenously calibrated (Favilukis et al. (2017)) and the change in the maximum PTI is chosen to match the remaining fraction of the change in household leverage. This generates a 19.50% decrease in the maximum LTV and a 49% decrease in the maximum PTI ratios (from 90% to 72% and from 58% to 29%). Simultaneously, the fixed and proportional mortgage origination costs $\{F_{m,t}, f_{m,t}\}$ increase from $1,200 to $2,000 and from 0.60% to 1%. Credit supply shocks take an additional period in 2018-21 ($t = 4$) to vanish which reflects the tightness of mortgage credit after the Great Recession. Credit shocks are identical across regions as in the data.[26]

While the model abstracts from other dimensions of credit standards as most quantitative models (e.g., FICO score requirements, asset and income verification),[27] an extension with housing valuation shocks is able to qualitatively replicate the increase in credit risk followed by a decrease, which these dimensions partly control in the data (Appendix C and Appendix Figure 24).

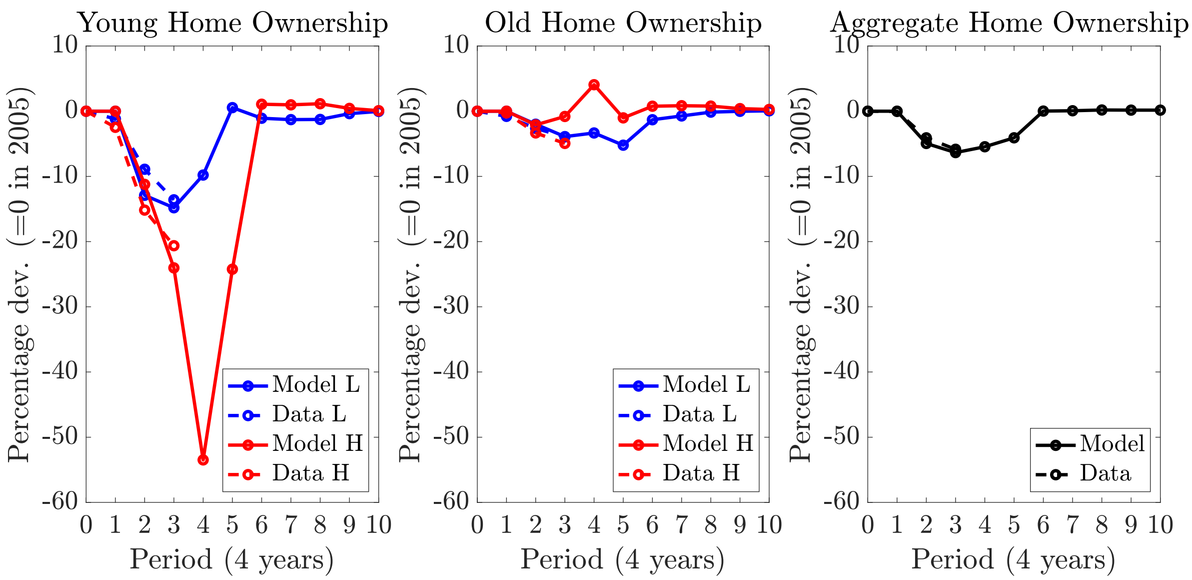
Home ownership Figure 8 decomposes the decrease in home ownership in response to the recession between age and region groups. It matches two features of the data. First, the decrease in home ownership is concentrated among young households (25-44 years old), as in Figure 1. Those households rely more on credit to buy homes than older ones who either already own or have accumulated more savings, as shown by their life-cycle profiles. Second, for young households, the decrease is concentrated in high-price metro areas, as in Figure 3. From 2005 to 2015, young home ownership decreases by 10% in Region L and by 20% in Region H. In contrast, old home ownership only falls by 5% in both regions (in the remaining of the text, the dynamics of old home ownership is plotted in in Appendix E). When aggregating metro areas, the model replicates the 8% decrease in average home ownership from peak (69%) to trough (63.4%). Importantly, the model generates significant regional heterogeneity in responses to the aggregate recession, despite the fact that regions are hit by identical credit shocks. There is no residual role

[26] Income data: Real Median Household Income in the United States, U.S. Census Bureau, Income and Poverty in the United States. Leverage data: aggregate leverage is measured as total mortgage debt outstanding to housing wealth in the Flow of Funds.

[27] E.g., Ambrose, Conklin and Yoshida (2016).

for changes in Millennials' preferences towards owning to explain the decrease in home ownership, consistent with survey evidence (Appendix A.8). Lastly, regional differences in home ownership busts are much larger than in local income. I show below that the latter has little effect on the dynamics of housing markets.

Figure 8: Home ownership response to aggregate recession with tight credit



Notes: Home ownership changes for 25-44 year old households (left panel), 45-85 year old households (middle), aggregate (right). Low-price MSAs in blue, high-price MSAs in red, economy average in black. Model: solid lines. Data: dashed line (source: ACS). Changes in percentage terms relative to 2005.

The model implies a larger and more persistent decrease in young home ownership in high-price metro areas. Because credit standards apply only at origination, their effect is close to zero in $t = 1$ and thus limited when they are first tightened. However, they ultimately lead to a 10% and a 55% decrease in young home ownership in low- and high-price metros, with a trough in $t = 4$ as the shock starts reverting. Their effect is persistent four years after the shocks have dissipated, but only in high-price regions, where young home ownership is still 25% lower in $t = 5$. In the absence of shocks in subsequent periods, young households eventually buy as they grow older, and new entrants buy at higher rates than previously constrained households at the same age.

The persistent decrease in home ownership after the Great Recession results from a decrease in households' propensities to buy, which translates into young buyers delaying home ownership. Appendix Figure 36 shows that the average probability for a renter to buy a house falls by up to 40% in low-price regions and 60% in high-price regions, where it stays persistently low even after the credit shock is over. The decrease is largest for young buyers in high-price regions and old buyers in low-price regions. However, because older households only represent a small fraction of new buyers, it is the decrease in young households' propensity to buy in high-price regions that explains most of the aggregate drop of 40%. The drop in households' entry rate into home ownership is 12 years more persistent than the 4-year increase in their exit rate through defaults, hence it is critical for the persistence of low home ownership after the recession.

House prices and rents Figure 9 plots the response of regional and aggregate house prices. The model matches the 10% price decrease in low-price MSAs, and about half of the 45% price decrease in high-price MSAs. Constructing the aggregate house price index as a value-weighted index of regional prices, the model generates a 17% decrease, more than two thirds of the 21% decrease in the data. Most of it is driven by high-price regions.

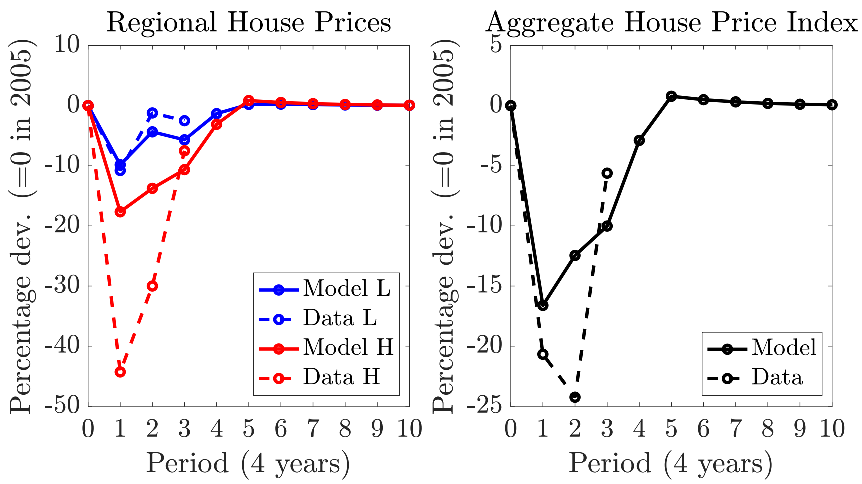
As for home ownership, regional differences in house price busts are not driven by heterogeneous credit contractions, but rather by heterogeneous responses to the same credit shocks. As I show below, heterogeneous income shocks only slightly amplify those regional differences, and they are unable to generate them when considered in isolation. This finding is in contrast with existing models of regional housing markets, where different local shocks are necessary to match differences in local house price busts. In an extended version of the model (Appendix C), I show that different valuation shocks Ξ_j^o to owner-occupied housing are only needed to match the remaining fractions of the house price bust in high-price metro areas. They are not needed to generate significant regional differences in house price busts.[28]

The recession initially generates a decrease in rents following the income shock, but then a sustained increase in both regions, in line with the data (Appendix Figure 35). The model generates close to the 5% increase in rents in low-price metros and the zero change in high-price metros in 2010-13. It predicts a subsequent persistent increase of almost 10% in both sets of regions, which is a general equilibrium response to lower income and tighter credit conditions. Because young households delay buying but have a higher housing consumption target because of the upward-sloping life-cycle profiles of income and wealth, they consume more rental services. This result is consistent with the evidence of a rental boom during the recovery from the Great Recession (Gete and Reher (2018)). As a result, rents recover two to three times faster than house prices.[29]

[28]Such shocks are required to match the dynamics of foreclosures in the data. Guren and McQuade (2020) study related shocks.

[29]These numbers are for detrended rents in the data, to make them stationary as in the model. Without

Figure 9: House price response to aggregate recession with tight credit



Notes: Left panel, house price changes in low-price MSAs (blue) and high-price MSAs (red). Right panel, aggregate house price change. Aggregate house price index calculated as the value-weighted average of regional house prices. Solid lines: model. Dashed lines: data (source: Zillow). Changes in percentage terms relative to 2005.

5.2 Regionally-Binding Credit Constraints

Nonlinear decomposition of credit and income shocks Appendix Figure 37 decomposes the contributions of income and credit shocks to the responses of home ownership and house prices across regions. It isolates the responses to an aggregate income, LTV, and PTI shock, and compares them to the responses in the baseline model, which combines these three shocks. The decrease in maximum PTI ratios (dashed line), which is identical across regions, is the main driver of the dynamics of young home ownership and house prices. It alone generates a 30% decrease in young home ownership in high-price MSAs (50% in the baseline) and a 15% decrease in house prices (17% in the baseline). Local income shocks alone (dotted line), which are more negative in high-price regions, only generate a 1% and a 2% decrease. The decrease in maximum LTV ratios (dashed-dotted line) has little effect.

In response to the shocks taken separately, young home ownership and house prices decrease in high-price MSAs, and they simultaneously increase in low-price MSAs because of spatial equilibrium. This result is due to the migration of some young buyers from high-price into low-price MSAs. It is absent from models of the aggregate housing market and from models with no migration, and consistent with empirical evidence on the "migration accelerator" (e.g., Howard (2019)). Identical credit shocks across regions generate the largest differences in migration responses. The model allows to quan-

detrending, raw rents always increase in the data, except in the first year after the Great Recession.

tify their impact on the region of destination and on the region of origin of migrating households, a challenge in the data. Home ownership and prices increase following in-migration, and decrease following out-migration. Migrations can amplify regional housing cycles in response to aggregate shocks.

Despite the positive effect of separate income and credit shocks in low-price metro areas, the total effect on home ownership and prices is negative in both regions in the benchmark model because of the interaction of the shocks. When households want to move from high-price to low-price regions to become home owners because of tighter credit, lower income make it harder for them to buy even in low-price regions. This effect is reinforced by the multiplicative interaction of tighter PTI ratios and lower incomes in home buyers' borrowing constraints, as Section 2.5 illustrated,

$$\overline{P} = \min\left[\frac{1-(1+r^b)^{-n}}{r^b}\theta_{PTI}Y + \text{downpayment}, \frac{\text{downpayment}}{1-\theta_{LTV}}\right]. \tag{27}$$

Life-cycle decomposition PTI constraints have a larger impact than LTV constraints on young home ownership. This result nuances popular narratives that solely attribute its decrease to high down payments requirements, and it is consistent with the wide use of low down payment mortgages among first-time buyers (government-backed FHA loans or conventional mortgages).[30]

First, the decrease in the maximum PTI ratio required to match the decrease in household leverage in the model is two to three times larger than for LTV, therefore its impact is larger all else equal. In the data, PTI constraints fell by more and more persistently too, while LTV constraints changed by little.[31]

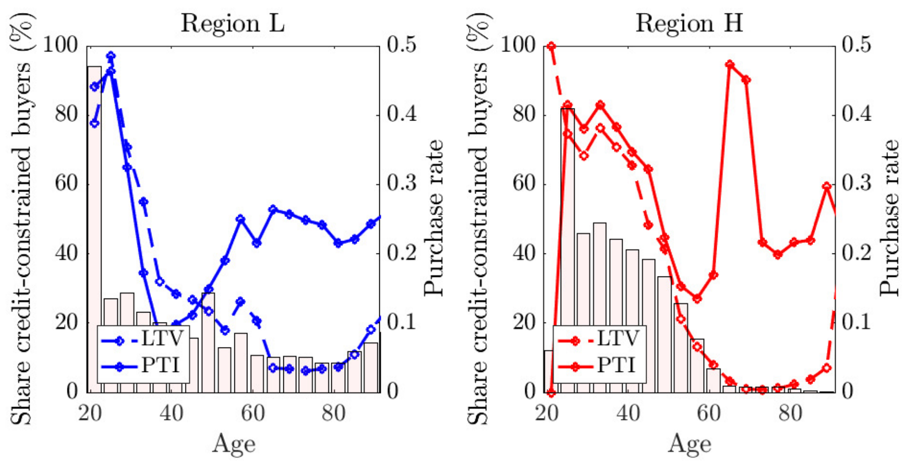
Then, PTI constraints bind for slightly more first-time buyers, with the exception of those below 29 years old. This is especially true for high-price MSAs where the decrease in young home ownership is concentrated. Figure 10 plots, for low-price and high-price MSAs (left panel, right panel), the shares of LTV-constrained and PTI-constrained first-time buyers over the life-cycle (dashed and solid lines on the left axes). Bars measure purchase rates by age (right axes), computed as the products of the fraction of renters and the average probability to buy conditional on age. The higher they are, the larger the

[30]See e.g. "'Its a lot tougher nowadays: Millennial homebuyers challenged with down payments and inventory", *Chicago Tribune*, 1/29/2020.

[31]As most macro-finance models (e.g., Favilukis et al. (2017)), the model requires larger changes in credit standards than in the data to match the decrease in household leverage. Between 2005 and 2017, the 90th percentile of the PTI distribution at origination fell from 55% to 45% while it fell from 102% to 98% for the combined LTV distribution ("Housing Finance at a Glance", *Urban Institute*, December 2019).

impact of constraints on the total response of local housing markets to the credit shock.[32]

Figure 10: Decomposition of first-time buyers' credit constraints



Notes: On left axes (both panels, in %), lines represent the shares of credit-constrained buyers at various ages for each type of constraint (PTI solid line, LTV dashed line). On right axes (both panels), bars represent purchase rates by age. Model values obtained using the stationary distribution of households in 2005. Left panel: low-price MSAs (blue). Right panel: high-price MSAs (red).

The transmission of shocks into home ownership is determined by three features of regional credit constraints. First, the share of credit-constrained buyers decreases with age as income and wealth grow until retirement. Second, there are more credit-constrained buyers in high-price MSAs (more than 70% of prime age buyers are constrained), except for the youngest buyers (21-24 years old) who are almost all constrained in low-price metros. Third, PTI constraints bind for slightly more buyers than LTV constraints in high-price MSAs, especially for 25-44 year old buyers with high purchase rates. LTV constraints bind more than PTI constraints in both regions only for the youngest buyers.

These features are due to the endogenous sorting of buyers across regions. Richer buyers tend to locate in high-price metros. In addition, renters tend to buy at older ages in those regions because house prices are higher. They have accumulated enough savings for a down payment at the time they buy. For the same reason, there are few older LTV-constrained buyers, since households tend to sort between regions early in their life-cycles.

[32] They decrease with age as more renters become owners, and are higher in high-price MSAs because they have more renters.

5.3 Time-Varying Transmission

The importance of regional credit constraints is time-varying, and increasing in preexisting differences in house price levels between regions. To illustrate how prices affect young buyers' credit constraints, Figure 11 plots responses for a counterfactual experiment with the less heterogeneous house price distribution of 1997. In that economy, aggregate and regional parameters are recalibrated to match the same targets as in the benchmark model, except for house price levels. In 1997, average house prices in Region L were \$95,000 (\$100,000 in 2005) and \$110,000 in region H (\$240,000 in 2005). The effect of regional credit constraints is muted: the less unequal distribution *ex ante* implies less unequal responses *ex post*, and a smaller aggregate bust. In 2005, the bust in young home ownership is amplified when credit contracts (-58% vs. -20% in 1997). In equilibrium, it also makes housing markets more volatile (prices fall by -18% vs. -14% in Region H). This result will imply that policies seeking to stabilize the aggregate housing market should focus on high-price regions.

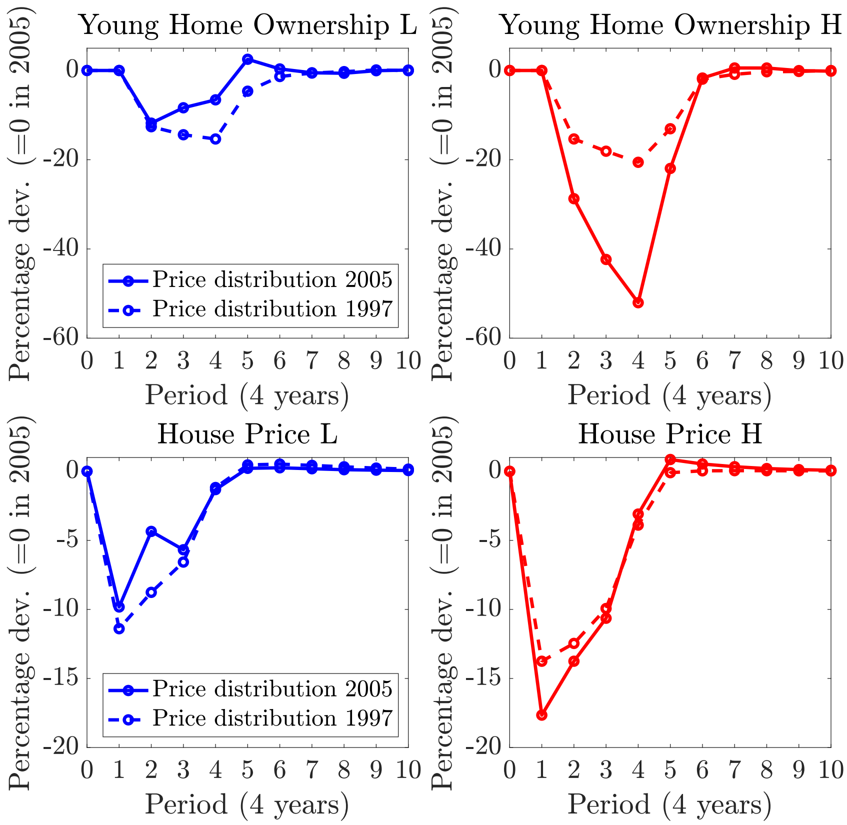
5.4 Geographic Microfoundation of Credit Constraints

The determinants of preexisting regional differences in house prices induce credit constraints to be more binding in high-price MSAs, and these markets to contract more in response to symmetric shocks. Table 5 shows steady state housing quantities and prices in a comparative statics analysis, which sets regional differences to zero for each set of parameters in isolation. Higher amenity benefits $\mathbf{\Xi^H} > \mathbf{\Xi^L}$ for rentals and owner-occupied units are responsible for house prices being on average \$80,237 higher in Region H in the benchmark, and for young home ownership being lower by 16 pp. Because young households who cannot afford high-price MSAs sort and buy in low-price MSAs, the young home ownership rate in those regions is slightly higher in the benchmark (+3 pp). The price is slightly lower because the marginal home buyer is poorer (-\$3,530).

The effects of housing supply differences on home ownership and house prices are sizable but lower. Differences in construction costs$1/\bar{I}_H > 1/\bar{I}_L$ contribute to prices being \$26,555 higher in high-price regions in the benchmark, with a slightly negative effect on young home ownership (-3 pp).[33] They contribute less than amenities to regional house price differences, hence to the importance of regional credit constraints. The price-elasticity parameter ρ_j has little effect on steady state levels, but it affects the dynamic

[33]Construction costs reflect physical and regulatory limits on housing supply, such as mountains and coasts, and permit approval time (e.g., Gyourko, Saiz and Summers (2008)).

Figure 11: Home ownership and house price responses to aggregate recession with tight credit under alternative house price distributions



Notes: On upper panels, responses of 25-44 year old home ownership under the 1997 house price distribution (dashed lines) and the 2007 distribution (benchmark, solid lines). On lower panel, house price responses. Blue: low-price MSAs. Red: high-price MSAs. Changes in percentage terms relative to 2005.

responses to the shocks.

Appendix Figure 39 plots the economy's transition dynamics in counterfactual scenarios without regional heterogeneity, in response to the same aggregate recession as in Section 5. It compares home ownership and house price responses when regional differences are set to zero for each set of parameters in isolation, to the benchmark with all the differences. Without differences in amenities ($\Xi^{\mathbf{H}} = \Xi^{\mathbf{L}}$), young home ownership falls by less than 20% in high-price MSAs instead of more than 50% in the benchmark. As a result, the busts in home ownership become almost identical across regions, at odds with the data. Regional differences in house price busts almost vanish (from a 9 pp difference in the benchmark to 3 pp). It makes it impossible for the model to generate an aggregate housing bust driven by high-price MSAs. Without differences in construction costs $\overline{I}_H = \overline{I}_L$, the responses of the two housing markets are also closer. However, the effect is weaker than for amenities (price differences fall from 9 pp in the benchmark to 5 pp), and

Table 5: Long-run housing market impact of regional heterogeneity

Variable	Benchmark	Same amenities	Same construction cost	Same housing supply elasticity
P_L	100,000	103,530	96,243	101,037
R_L	1,010	1,074	898	972
ho_L^{young}	0.57	0.54	0.52	0.55
ho_L^{all}	0.69	0.74	0.66	0.68
P_H	240,000	159,763	213,445	238,435
R_H	1,415	1,656	768	1,090
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 MSAs have higher amenity benefits, higher construction costs, a lower price-elasticity of housing supply. Comparative statics analysis: columns after "Benchmark" show the steady state values of the variables of interest when setting each of these parameters in isolation equal to their values in low-price MSAs. "Same amenities": $\Xi_H = \Xi_L$. "Same construction costs": $\overline{I_H} = \overline{I_L}$. "Same supply elasticity": $\rho_H = \rho_L$. Prices and rents are in 1999 dollars.

it is even lower for housing supply elasticity differences (when $\rho_H = \rho_L$, price differences fall from 9 pp in the benchmark to 7 pp). Overall, amenity differences contribute as much to regional differences in housing busts in the short run as differences in housing supply costs and elasticities combined.

6 Cohort Effects

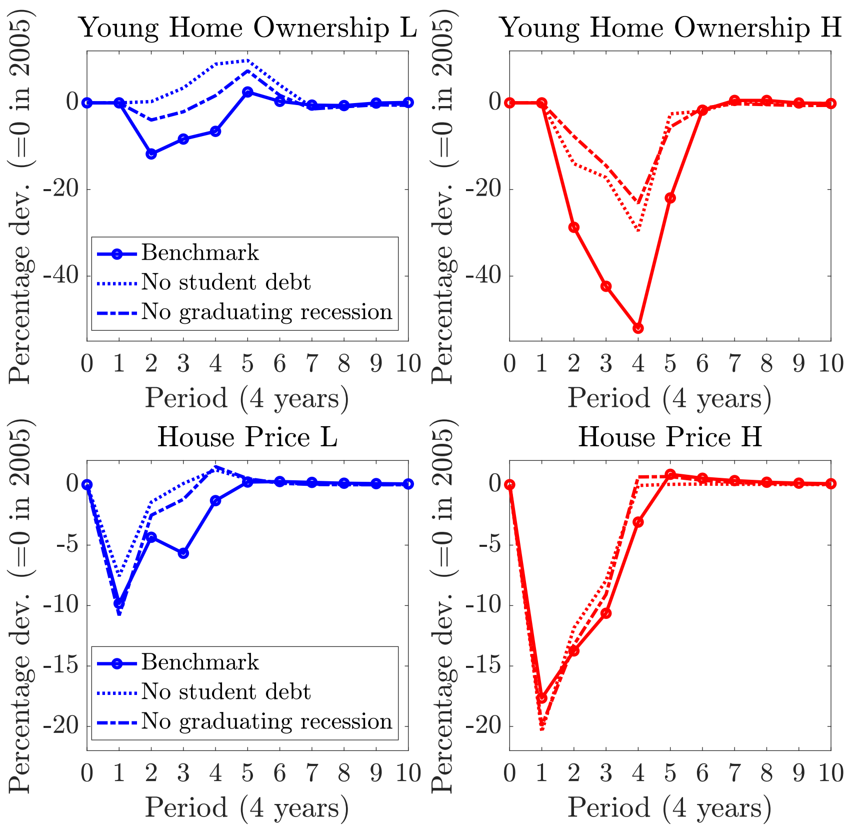
After studying how aggregate credit contractions make borrowing constraints more binding, this section turns to their determinants at the household level: income, wealth, and the option to relax regionally-binding constraint by moving between regions.

6.1 Income Scarring and Student Debt

While both factors are popular explanations for low home ownership rates in the Millennial cohort, they have been studied separately so far (e.g., Bleemer et al. (2021)). I study them jointly and show that regional heterogeneity is crucial to evaluate their total impact on housing markets. In the baseline model, Millennial households (i) have lower wealth in their twenties and early thirties, calibrated to reflect student debt burdens; (ii) draw their initial income from a distribution that is first-order stochastically dominated by the distribution in normal times, which lowers their entire income profile because of the persistence in the idiosyncratic process.

Figure 12 shows the cohort effects on housing market volatility. It plots the responses of young home ownership and house prices to the aggregate recession in counterfactual transitions without student debt and income scarring. These two features amplify the decrease of young home ownership in high-price MSAs by a factor of two. Without them, young home ownership would even increase in low-price MSAs in response to the recession, at odds with the data. Thus abstracting from Millennial-specific features would bias the inference on the effects of the recession on housing markets. Consistent with LTV constraints binding more in low-price MSAs, the negative effect of student debt on home ownership is relatively larger in those regions (-15 pp) since it slows down wealth accumulation for a down payment. Consistent with PTI constraints binding more in high-price MSAs, the recession's scarring effect on earnings is relatively larger (-25 pp).

Figure 12: Home ownership and house price responses to aggregate recession with tight credit without cohort differences



Notes: On upper panels, responses of 25-44 year old home ownership in the benchmark (solid lines), the benchmark without Millennial student debt (dotted lines), the benchmark without the recession's scarring effect on Millennial earnings (dashed lines). On lower panel, house price responses. Blue: low-price MSAs. Red: high-price MSAs. Changes in percentage terms relative to 2005.

Turning to their long run impact, Table 6 presents steady state home ownership and prices in counterfactual economies where these features are turned off in isolation. Qualitatively, the impacts of student debt and income scarring are the same. The former directly lowers wealth, hence makes LTV-constrained more likely to bind. The latter lowers income, hence makes PTI constraints more likely to bind. Through wealth accumulation, it also lowers savings and make LTV constraints more likely to bind. Therefore, they both decrease home ownership and prices nationwide. Quantitatively, income scarring has a larger impact. In high-price MSAs, home ownership would be 2 pp higher without student debt and 6 pp higher without income scarring. In both regions, house prices would be around 2% and 6% higher without them respectively.

There are substantial regional differences in young buyers' responses. Student debt and income scarring decrease the young home ownership rate by 8 pp and 15 pp in high-price MSAs, but they increase it by 17 pp and 8 pp in low-price MSAs. This effect is again due to spatial sorting: worse life-cycle features lead some young buyers to relocate from high-price to low-price MSAs. Without these cohort effects, Millennials would stay in high-price MSAs and wait until they have sufficient savings and income to buy. This result is consistent with growing evidence on Millennial buyers leaving high-price MSAs since the recession and buying in less expensive areas, where they contribute to local housing booms.[34] Within high-price areas, Millennials who do not relocate consume more rental services, which generates a long-run boom in rents. I estimate that student debt boost rents in high-price MSAs by 8.3%.

Table 6: Long-run housing market impact of cohort differences and mobility

Variable	Benchmark	No student debt	No graduating in recession	Free mobility	No mobility
P_L	100,000	102,046	106,282	100,069	116,615
R_L (\$)	1,010	1,174	1,112	1,523	673
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	240,000	245,911	254,565	220,429	188,042
R_H	1,415	1,307	1,344	1,546	2,210
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: In the benchmark model, Millennial households entering the economy during the recession have student debt and persistently lower lifetime income because of graduating in bad times; the moving cost $m \in (0, \infty)$ generates positive but limited mobility between regions. Comparative statics analysis: columns after "Benchmark" show the steady state values of the variables of interest when setting separate cohort differences between Millennials and other household types to zero. "Free mobility": $m = 0$. "No mobility": $m = \infty$. Prices and rents are in 1999 dollars.

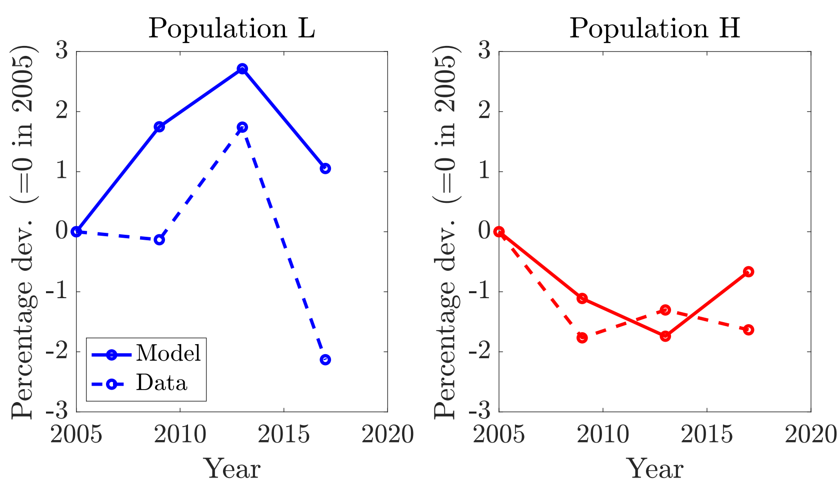
[34] See Frey (2019).

6.2 Frictions to Spatial Arbitrage

I conclude this section by studying how the response of housing markets to the recession depend on household mobility between regions.

Figure 13 plots population changes in the two types of metro areas since the Great Recession in the model and the data. The model generates realistic population flows in response to the recession, hence produces credible estimates of spatial equilibrium effects. It exactly matches the 2% population decline in high-price metros, and slightly overestimates the 1.5% increase in low-price metros. The previous section has shown that these flows have a significant effect on housing markets, despite being relatively small.

Figure 13: Population response to aggregate recession with tight credit



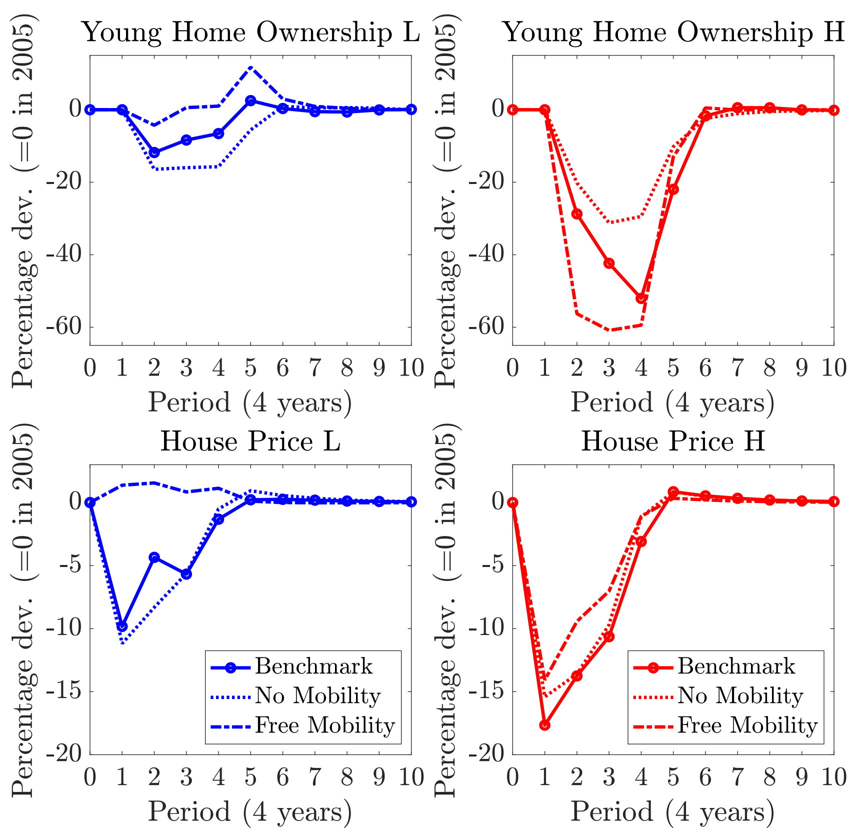
Notes: Model changes: solid lines. Data changes (dashed lines) are calculated as deviations from their 2005 values, from which the aggregate trend (also in deviation from 2005) is subtracted to control for the increase in total population. The resulting series are thus normalized to 0 in 2005. Similar results are obtained with unweighted and population-weighted averages by MSA groups. Low-price MSAs in blue, high-price MSAs in red. Source: ACS.

As Figure 14 shows, mobility amplifies the decrease in young home ownership in high-price MSAs, with estimates in the benchmark (-55%) lying between the model with no mobility (-30%) and free mobility (-60%). However, it leads to an increase in low-price MSAs because some buyers relocate and buy in those areas, which dampens the total decrease in young home ownership. In contrast, young home ownership in both regions falls significantly in the benchmark, where relocation between regions is limited because of the migration cost and the option to rent in households' region of origin. Overall, these frictions to spatial arbitrage amplify the bust in young home ownership.[35]

[35] As for all experiments in this paper, the effect of mobility on older households is ambiguous and much smaller (Appendix Figure 41). Older agents are less mobile in steady state and in response shocks because the fixed utility cost of moving represents a relatively larger fraction of their remaining lifetime utility.

In Table 6, the last two columns quantify the long-run effect of frictions due to the moving cost m. The benchmark lies between two polar cases of no mobility ($m = +\infty$) and free mobility ($m = 0$). Without mobility, differences between housing markets would be attenuated. For instance, prices would be +16.6% higher in low-price MSAs and -21.6% lower in high-price MSAs. This is because under the same initial distributions of households as in the benchmark, richer households who would have moved from low-price to high-price MSAs are forced to stay in the former, while poorer households who would have moved from high-price to low-price MSAs are forced to stay in the latter. Marginal home buyers who determine prices would then be respectively richer and poorer.

Figure 14: Effect of mobility on home ownership and house price responses to aggregate recession



Notes: On upper panels, responses of 25-44 year old home ownership in the benchmark with positive but limited mobility (solid lines, $m \in (0, \infty)$), no mobility (dotted lines, $m = \infty$), free mobility (dashed lines, $m = 0$). On lower panel, house price responses. Blue: low-price MSAs. Red: high-price MSAs. Changes in percentage terms relative to 2005.

7 First-Time Buyer Subsidies

This section concludes by analyzing the effect of regional credit constraints on the effectiveness of housing stabilization policies in response to aggregate credit contractions. I focus on the First Time Homebuyer Credit (FTHC) of 2009, whose impact has not yet been evaluated in a structural model. I compute estimates of the impact of the policy which account for spatial and general equilibrium effects and complement empirical estimates of local average treatment effects. I use them to understand its impact on buyers' welfare. I then show how place-based subsidies can improve its effectiveness.

7.1 The First-Time Home Buyer Credit

Background I focus on the second version of the 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 bust. The policy is financed by the issuance of long-term government bonds such that the government budget constraint does not affect the current cohorts. I compare the economy's transition in response to the recession with ("FTHC") and without the subsidy ("Bench").

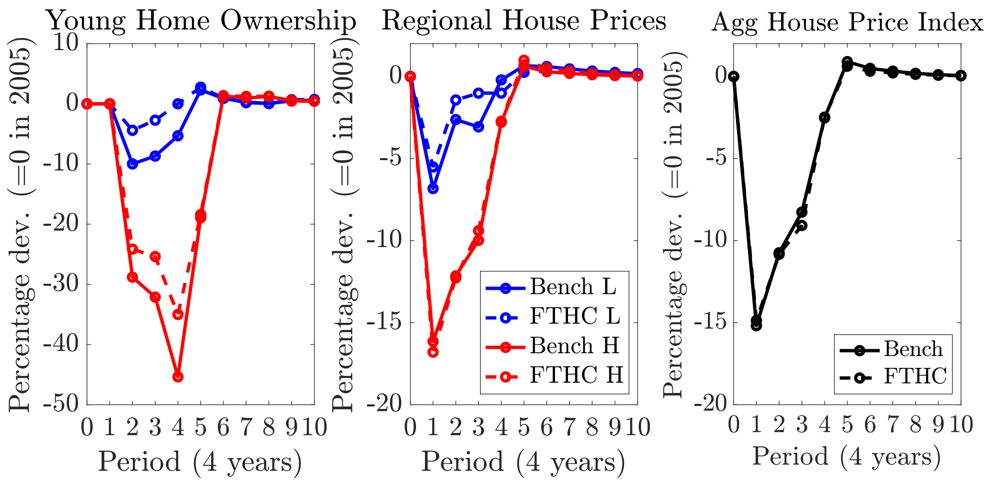
Dampening through regional heterogeneity Figure 15 shows the dynamic impact of the policy. It has a stabilizing effect on young home ownership (-5% instead of -10% in low-price MSAs and -35% instead of -45%) and on house prices. The subsidy directly makes LTV constraints less likely to bind, and indirectly makes PTI constraints less likely to bind because buyers need to borrow less. It stabilizes young home ownership by 5 pp in low-price regions and 10 pp in high-price regions, resulting in an increase in home sales of about 10%.[36] It stabilizes the aggregate price index by about 1 pp, an effect coming mostly from dampening the price decline in low-price MSAs. These effects are in line with empirical estimates (Berger et al. (2019)).

The policy is effective at stabilizing low-price MSAs, by cushioning half of the decrease in young home ownership and one seventh of the house price decrease. However, it fails to stimulate high-price regions relatively as much, by cushioning less of one fourth of the decrease in young home ownership and having virtually no impact on prices. Therefore its effect on aggregate house prices is limited. Because it is identical across regions, the

[36]In the model, the increase in home sales consists of more sales from older to younger households and of more residential investment. In the data, the increase also came from a decrease in the stock of existing vacant homes.

subsidy represents a lower fraction of house prices in high-price than in low-price MSAs (8% vs. 3.3%). It relaxes local credit constraints for more buyers in the latter. However, since the decrease in young home ownership is concentrated in high-price MSAs, the subsidy does not stabilize enough those regions that are most responsible for the bust.

Figure 15: Impact of First-Time Homebuyer Credit on home ownership and house prices



Notes: Solid lines represent the benchmark responses without the policy. Dashed lines represent responses with the policy. In both cases the economy is subject to the same sequence of income and credit shocks as in the benchmark. Left panel: change in young home ownership (low-price MSAs in blue, high-price MSAs in red). Middle panel: house prices. Right panel: aggregate house price index (black).

7.2 Buyers' Welfare

Instead of a "one size fits all" subsidy across regions in dollar terms, I estimate welfare the impact on an identical proportional subsidy which scales with local house prices, chosen to be government budget-neutral. Because of regional price differences, such a policy is effectively a place-based policy which increases the dollar amount received by first-time buyers in high-price MSAs, and decreases it in low-price MSAs.

Uniform subsidy Figure 16 plots the dynamic welfare impacts of the uniform ("FTHC") and the place-based subsidies ("PB"). Consumption-equivalent variations measure the net welfare gains of the policies in terms of four years of non-durable consumption (one period).[37] The baseline policy generates a sizable aggregate welfare gain (average, black lines), corresponding to a 1.5% increase in four-year consumption. Welfare gains come

[37] See Appendix B.3 for more detail.

from four sources: owning allows buyers to live in larger units, enjoy higher amenity benefits, hedge against rent increases, and quickly accumulate wealth when the rate of return on housing increases. The policy also slightly improves the recovery of non-durable consumption. (Appendix Figure 42). Gains are larger several years into the recession when the decrease in home ownership is larger, and they are heterogeneous across households. The policy only benefits renters who buy a house, with a limited effect on owners' welfare. It benefits more buyers in high-price MSAs, because amenity benefits conditional on buying are larger. However it has a lower effect on the number of buyers in those regions, which dampens its total welfare effect.

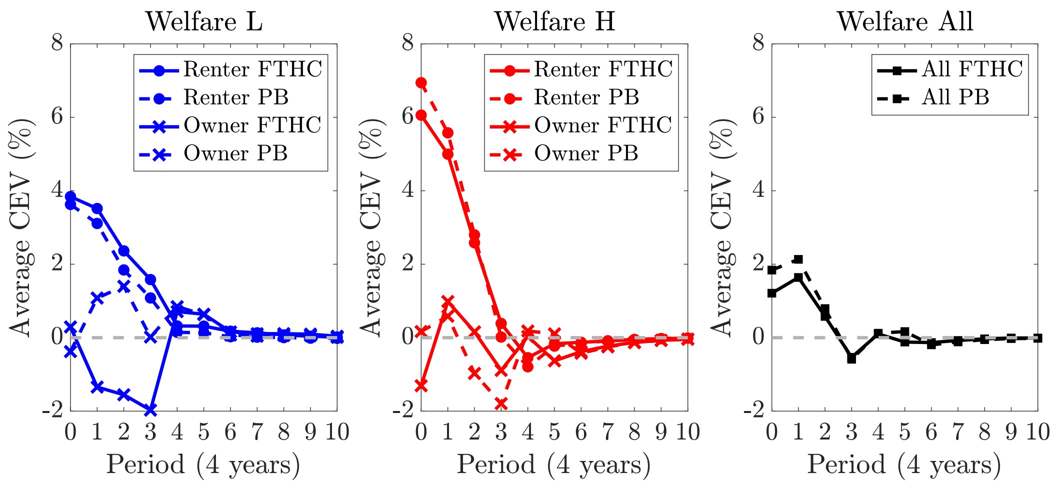
Place-based subsidy Relative to the uniform policy, place-based subsidies increase aggregate welfare by a third. This is achieved by an increase in the welfare of buyers in high-price regions and an increase in the size of this group because the policy makes buying more affordable. Though the policy is not a Pareto improvement, this increase dominates the small welfare losses of buyers in low-price MSAs, and improves the total effectiveness of the policy. Two factors explain this increase. First, calibrated utility benefits $\Xi_{\mathbf{H}}^{\mathcal{H}}$ of living and owning in high-price MSAs are larger, which makes welfare gains larger for a given increase in local home ownership. Second, the place-based subsidy is larger in high-price MSAs, therefore it stabilizes young home ownership more than the uniform subsidy, applying the larger utility benefits to a larger population. This result suggests that the design of housing stabilization policies should not only account for buyers' income and wealth, which would lead to target low-price MSAs, but also for local house prices and location preferences, which rather lead to target high-price MSAs.

8 Conclusion

Low home ownership rates among Millennials are one of the main features of the post-Great Recession period. This paper shows that to understand their causes and consequences for households' balance sheets, house prices and rents, and stimulus policies, it is critical to account for regional differences between markets. I obtain these findings in a novel setting, which explicitly connects an equilibrium spatial macro-finance model with heterogeneous buyers and incomplete markets to a panel of U.S. metro areas.

Because young buyers are more financially constrained in regions with higher prices, they disproportionately respond to changes in credit standards by delaying home pur-

Figure 16: Welfare effect of First-Time Homebuyer Credit and place-based subsidy



Notes: Solid lines represent conditional welfare gains from the First-Time Homebuyer Credit. Dashed lines represent conditional gains from a place-based subsidy, defined as a fixed percentage of local prices in the steady state. In both cases the economy is subject to the same sequence of income and credit shocks as in the benchmark. Welfare effect of policies measured relative to the benchmark as consumption-equivalent variations (for four years). Left panel: welfare gains in low-price MSAs (blue). Middle panel: welfare gains in high-price MSAs. Conditional average gains are plotted separately for renters (dots) and owners (crosses). Right panel: aggregate welfare gains, computed with a utilitarian social welfare function.

chases, resulting in larger busts. Limited access to credit prevents them from arbitraging local house price busts which would generate high returns. But also, spatial frictions prevent them from arbitraging regional price differences by moving en masse to lower-price regions. The vastly heterogeneous dynamics of local markets after the recession is not explained by larger local shocks to income or credit, but rather by the larger impact on high-price regions of the same credit contraction nationwide (period effect). Cohort effects such as higher student debt and income scarring persistently hamper housing markets and reduce the importance of housing on households' balance sheets, though not as much as the initial drop in young home ownership would suggest, and they tend to benefit lower-price housing markets. Subsidies to first-time buyers following a credit contraction partly undo these negative period and cohort effects, but not enough if they are identical across regions as the First-Time Homebuyer Credit.

Place-based subsidies to first-time buyers which target high-price regions, with larger busts, are more effective. This is an important dimension in which housing stabilization policies differ from traditional place-based labor market policies, which tend to target low-income regions. This result is, however, less surprising in light of real-world housing policies. For instance, several first-time buyer programs in the U.S. differ across regions and offer lower rates, down payment requirements, or direct subsidies (e.g., "Achieving the Dream" in the New York State). Future work could use this framework to analyze them as well as other credit-ameliorating policies with a regional dimension. Understanding how buyers' migrations to the suburbs and the countryside associated with the recent increase in working from home affect local housing markets would be another interesting direction.

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Appendix

A Data Appendix

A.1 Dataset Construction

To construct the regional panel dataset, 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 HMDA, and Fannie Mae and Freddie Mac through Recursion Co, a financial analytics firm which aggregates 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[38]. 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.

I also 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 Rico).

A.2 Additional data sources

These data sources supplement those described in the main text, and are used in the calibration of the model and in the facts documented 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

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

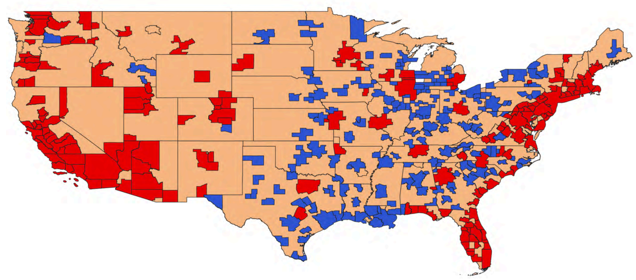
in the construction sector (NAICS code 23 and subcodes). I also use MSA-level data on housing supply elasticity as estimated by Saiz, which are do not vary by year.

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 (available upon request). 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 Classifying Regions

The first group includes regions with historically stable house prices, unconstrained housing supply, and in low demand from buyers. The second group includes regions with historically higher volatility and tight housing supply restrictions, and regions with historically stable prices that experienced high volatility during the 2000s. All high-price regions are in high demand.

Figure 17: Regional distribution of house price levels



Source: Zillow. This map plots the distribution of MSAs sorted by house price levels in 2005, bottom 50% in blue and top 50% in red.

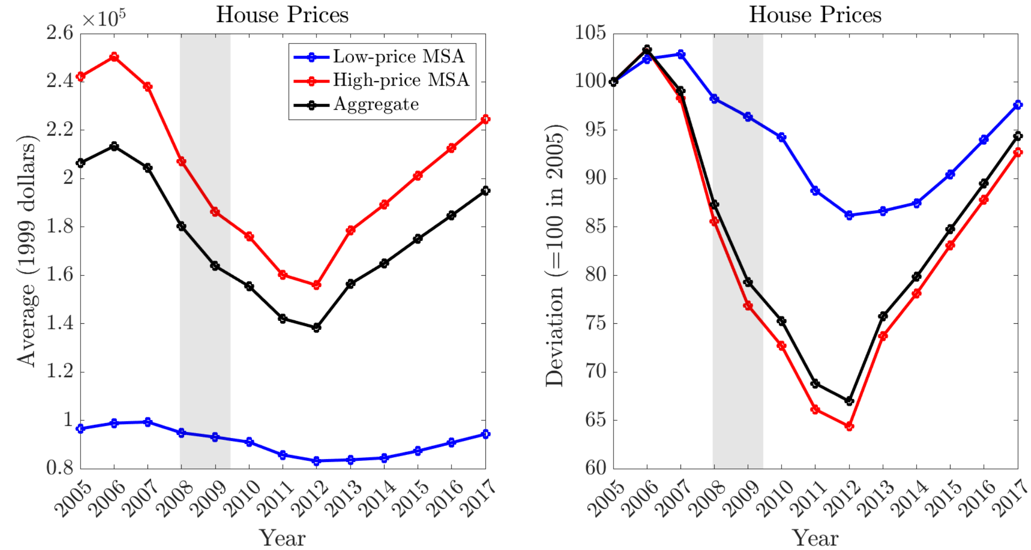
Table 7: MSA group: bottom 50% of the 2005 house price distribution

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 8: MSA group: top 50% of the 2005 house price distribution

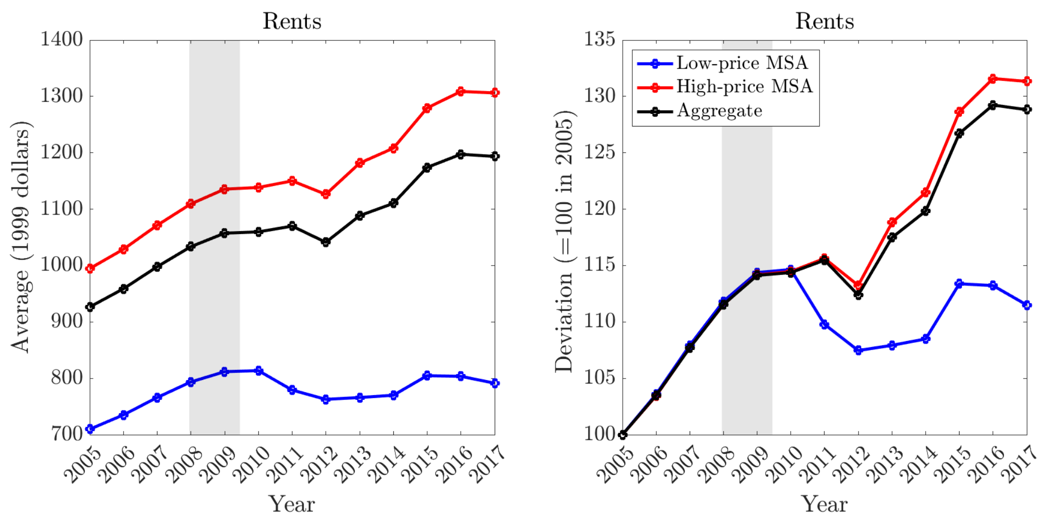
Top 50%
Albany, OR ; Albany-Schenectady-Troy, NY ; Albuquerque, NM ; Allentown-Bethlehem-Easton, PA-NJ ; Anchorage, AK ; Ann Arbor, MI ; Asheville, NC ; Atlanta-Sandy Springs-Marietta, GA ; Atlanta-Sandy Springs-Roswell, GA ; Atlantic City, NJ ; Atlantic City-Hammonton, NJ ; Auburn-Opelika, AL ; Austin-Round 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 ;

Figure 18: House price dynamics by region group



Notes: Levels, 1999 dollars (left panel) and deviation from 2005 value, normalized to 100 (right panel). MSAs are sorted into two groups by the level of house prices in 2005 (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 2005. The shaded area indicates the NBER recessions. Sources: Zillow, ACS.

Figure 19: Rent dynamics by region group



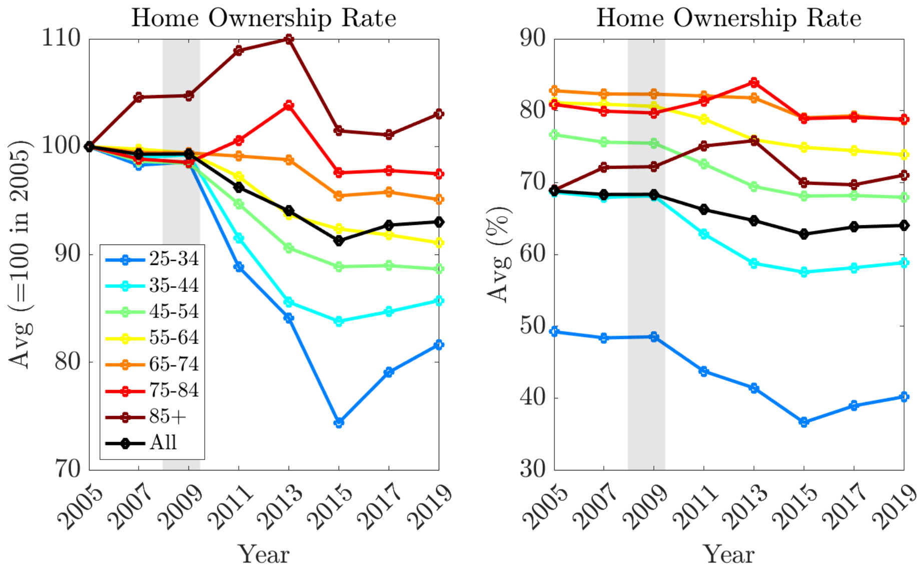
Notes: Levels, 1999 dollars (left panel) and deviation from 2005 value, normalized to 1 (right panel). MSAs are sorted into two groups by the level of house prices in 2005 (bottom 50%, blue, and top 50%, red). Within each group, the weighted average rate of a given age group is calculated using the MSA total population in 2005. The shaded area indicates the NBER recessions. Sources: 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.

A.4 Age Decomposition of Home Ownership

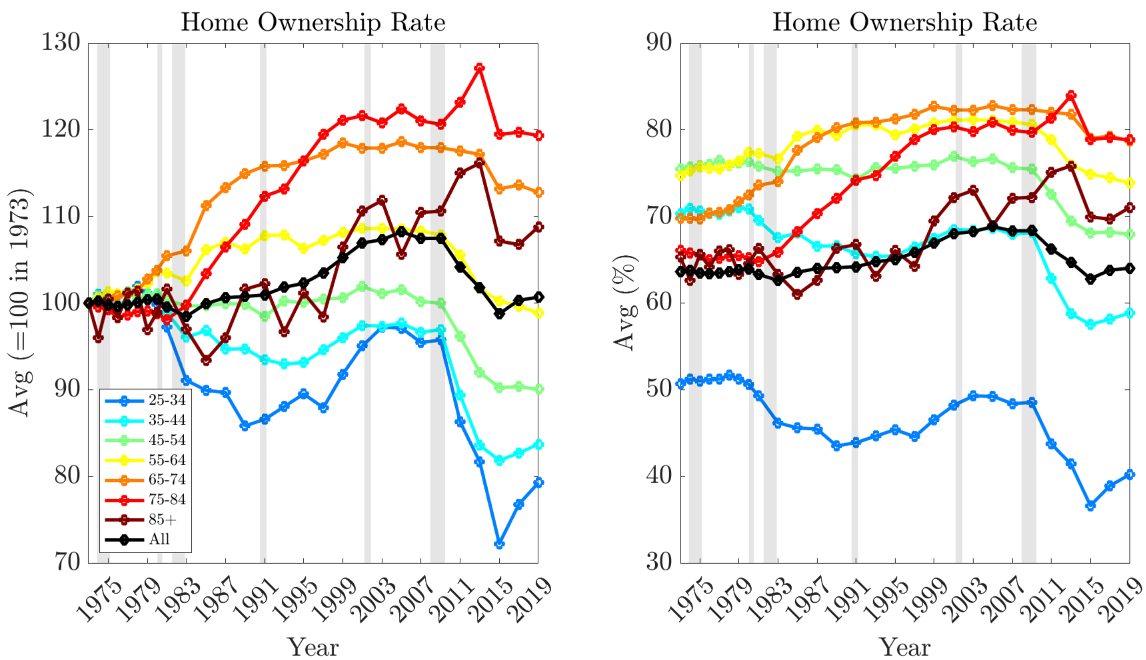
Figure 20: Home ownership by age group (detailed decomposition)



Notes: Home ownership rate by age group. Left panel: change, values normalized to 100 in 2005. Right panel: level. Population-weighted averages. Gray bands indicate NBER recessions. Sources: AHS.

A.5 Demographic Determinants of Home Ownership Changes

Figure 21: Home ownership by age group (detailed, long-run decomposition)



Notes: Home ownership rate by age group. Left panel: change, values normalized to 100 in 1973. Right panel: level. Population-weighted averages. Gray bands indicate NBER recessions. Sources: AHS.

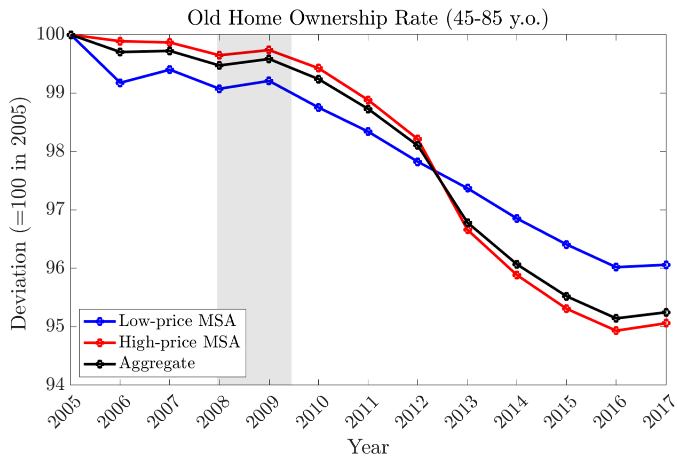
Table 9: Population groups with largest decrease in home ownership since 2005, by determinant of home ownership

Home ownership rate	2005-15 change (pp)
All	-6.1
Age	
25-34	***-14.7***
15-24	***-13.1***
Income	
Q3	-7.4
Q1	-6.4
Race	
Black	-6.3
White	-5.0
Education	
Less than high school	-8.5
Some post-secondary	-8.4
Household composition	
Female single householder, with kids	-9.7
Married couple with kids	-8.3

Source: AHS. This table shows the result of a single unconditional sort of changes in home ownership rates (in percentage points) by population groups corresponding to classical determinants of home ownership (Goodman and Mayer (2018)). For each group, the largest two changes by subgroup are shown. Young households highlighted, as group for which home ownership fell the most.

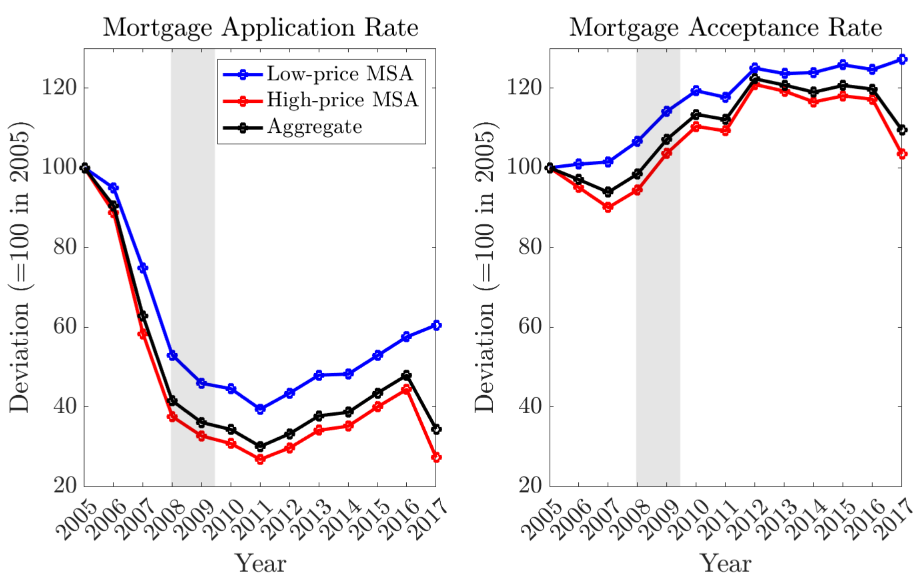
A.6 Additional Figures: Changes

Figure 22: Change in old home ownership



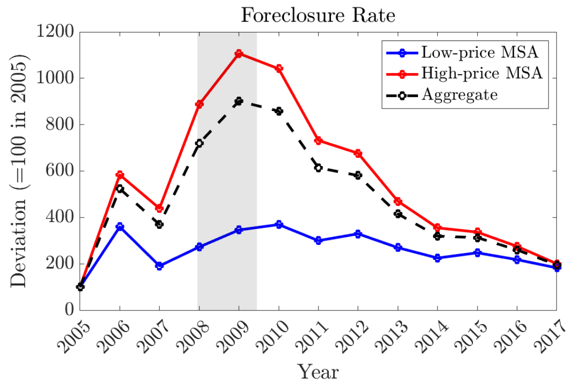
Notes: The solid lines depict the average home ownership rate of 45-85 years old buyers in low- (blue) and high-price MSAs (red). The black line depicts the economy average. Variables normalized to 100 in 2005. Population-weighted averages. Gray bands indicate NBER recessions. Source: ACS, Zillow.

Figure 23: Changes in mortgage application and acceptance rates



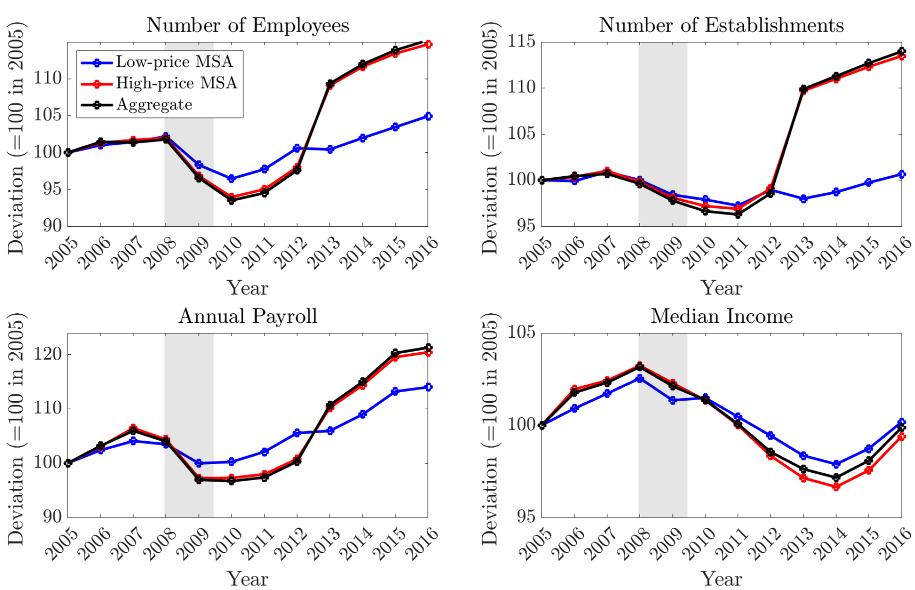
Notes: Left panel, changes in purchase mortgage application rates in low- (blue) and high-price MSAs (red), calculated as the ratio of the number of mortgage applications to buying-age population. Right panel, changes in purchase mortgage acceptance rates, calculated as the ratio of the number of mortgage applications accepted to the number of applications. Black line depicts the economy average. Variables normalized to 100 in 2005. Population-weighted averages. Gray bands indicate NBER recessions. Source: ACS, HMDA, Zillow.

Figure 24: Change in foreclosure rates



Notes: Changes in foreclosure rates in low- (blue) and high-price MSAs (red). Black line depicts the economy average. Variables normalized to 100 in 2005. Population-weighted averages. Gray bands indicate NBER recessions. Source: RealtyTrac, Zillow, ACS.

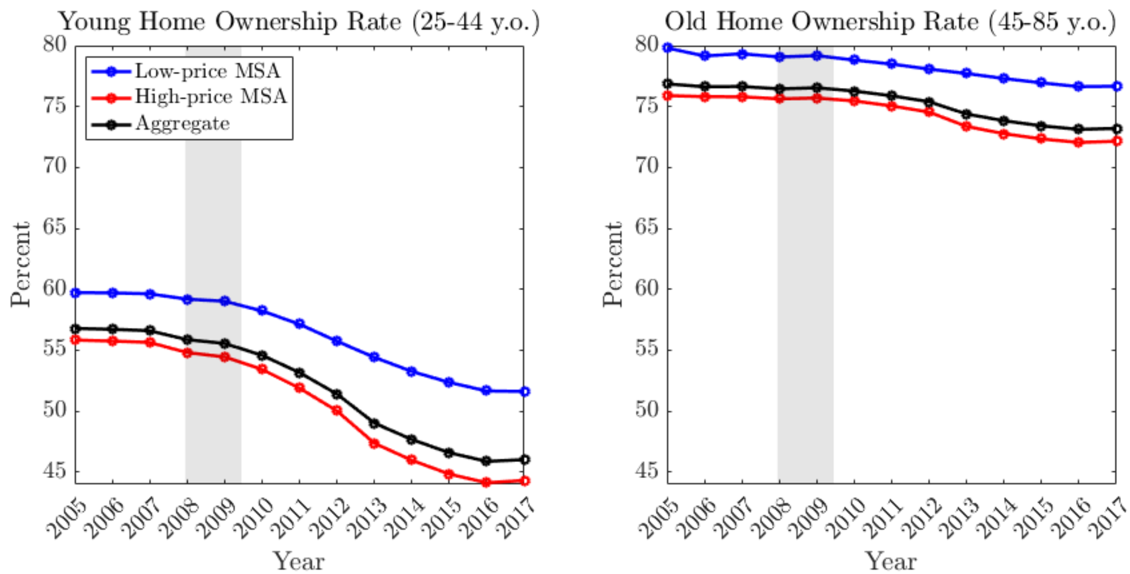
Figure 25: Labor market changes



Notes: Changes in number of employees (upper left panel), number of establishments (upper right), total annual payroll (lower left), median worker income (lower right) in low- (blue) and high-price MSAs (red). Black lines depict the economy average. Population-weighted averages. Gray bands indicate NBER recessions. Source: CBP, ACS, Zillow.

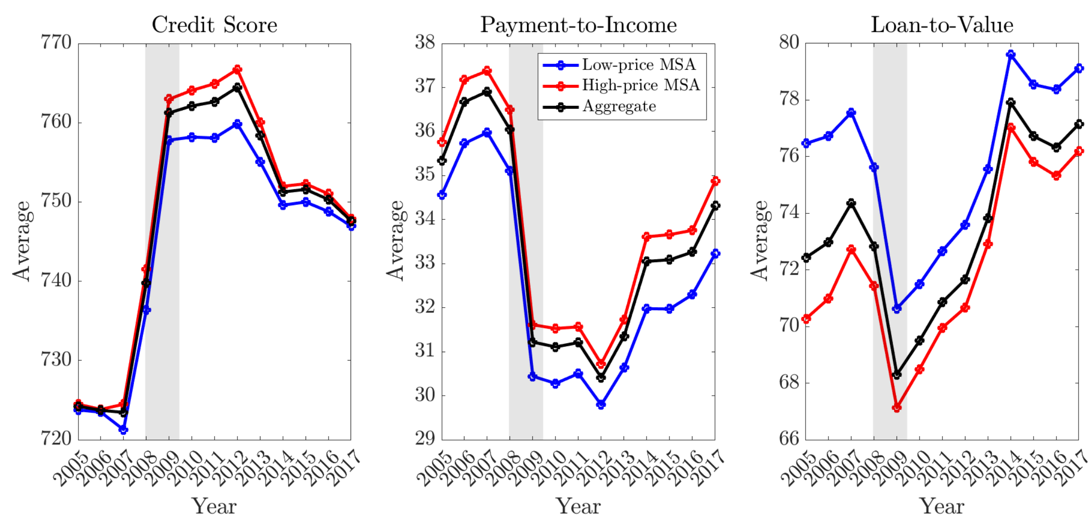
A.7 Additional Figures: Levels

Figure 26: Home ownership rates by age



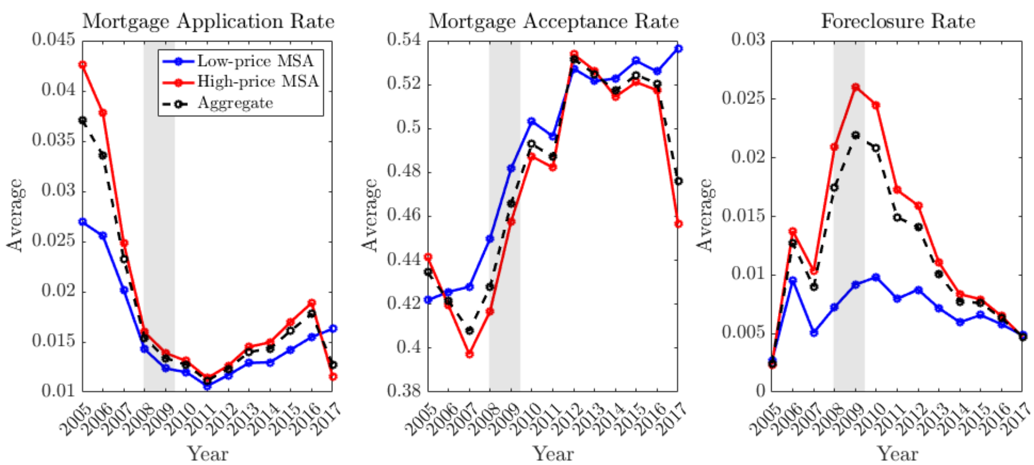
Notes: Left panel, home ownership rate for young households (25-44 y.o.) in low- (blue) and high-price MSAs (red). Right panel, home ownership rate for older households (45-85 y.o.). The black line depicts the economy average. Population-weighted averages. Gray bands indicate NBER recessions. Source: ACS, Zillow.

Figure 27: Credit conditions



Notes: Top percentiles (P75) of the distributions of credit scores (right panel), Payment to income ratios (middle, in %), loan to value ratios (right, in %) in low- (blue) and high-price MSAs (red). Black lines depict the economy average. Population-weighted averages. Gray bands indicate NBER recessions. Source: ACS, Zillow.

Figure 28: Loan application rate, rejection rate, foreclosure rate



Notes: Left panel, purchase mortgage application rates in low- (blue) and high-price MSAs (red), calculated as the ratio of the number of mortgage applications to buying-age population. Middle panel, purchase mortgage acceptance rates, calculated as the ratio of the number of mortgage applications accepted to the number of applications. Right panel, foreclosure rates. Black line depicts the economy average. Population-weighted averages. Gray bands indicate NBER recessions. Source: Fannie Mae, Freddie Mac, RealtyTrac, ACS, Zillow.

A.8 Millennial Attitudes Towards Home Ownership

Using three different measures, I find that there is no role for changes in Millennials' preferences towards home ownership relative to previous cohorts to explain their lower home ownership rates. Unlike attitudes towards financial markets after the Great Depression described by Malmendier and Nagel (2011), the Great Recession does not seem to have changed young households' attitudes towards home ownership.

First, this finding comes from direct evidence from three surveys directly asking Millennial households about their preferences in the 2010s. In the Survey of Consumer Expectations Housing Survey (Federal Reserve Bank of New York), the question "Would you like to own instead of rent your primary residence" gives 71.3% yes (19.4% no); "Compared to other financial investments, buying in your zip code today is" gives 64.9% good (9.1% bad). Responses are similar in the Housing Confidence Survey (Pulsenomics), which asks "Is housing a good long-term investment?", and in the National Housing Survey (Fannie Mae).

Second, this finding is confirmed by indirect measures in household-level data. If Millennial's preferences towards owning have decreased, then financially-unconstrained households should have lower home ownership rates than previous cohorts. I find that this is not the case. I focus on prime-age white households in the ACS, aged 25-34 years old, married with children, and with annual income greater than $100,000. I find that their home ownership rate has decreased significantly less (-2.8 pp) than for all households in 1990-2015.

Third, in line with these findings, the quantitative analysis conducted in the model finds no residual role for changes in preferences to explain the decrease in home ownership, once the effect of credit conditions and objective cohort differences has been accounted for.

B Model Appendix

B.1 Environment

Pension schedule The pension schedule replicates key features of the U.S. pension system by relating last period income to average income over the life-cycle to compute retirement benefits (Guvenen and Smith (2014)). Denote 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. Using income retirement to define pension benefits allows to save a state variable in the dynamic programming problem. Retirement income is equal to:

$$Y_{i,R} = \overline{Y} \times \begin{cases} 0.9\tilde{Y}_{i,R} & \text{if } \tilde{Y}_{i,R} \leq 0.3 \\ 0.27 + 0.32(\tilde{Y}_{i,R} - 0.3)\tilde{Y}_{i,R} & \text{if } 0.3 < \tilde{Y}_{i,R} \leq 2 \\ 0.81 + 0.15(\tilde{Y}_{i,R} - 2)\tilde{Y}_{i,R} & \text{if } 2 < \tilde{Y}_{i,R} \leq 4.1 \\ 1.13 & \text{if } 4.1 \leq \tilde{Y}_{i,R} \end{cases} \tag{28}$$

Millennial student debt schedule Average student debt levels by productivity and age groups are chosen to match their values by income percentiles in the 2016 Survey of Consumer Finances and by age in the 2020 Federal Student Loan Portfolio of the U.S. Department of Education.

Table 10: Student debt by income percentiles

Income percentile	P0-P25	P25-P50	P50-P75	P75-P90	P90-P100
Average debt (dollars)	26,000	34,200	34,700	41,200	46,070

Source: Survey of Consumer Finances, 2016.

Table 11: Student debt by age group

Age group	21-24	25-34	35-49
Average debt (dollars)	14,800	33,800	42,300

Source: U.S. Department of Education, 2020.

B.2 Home Owner Problem

Denote the date t value function of an owner starting the period in region L, as $V^{oL}(a, b_t, y_t)$. It chooses to either remain an owner, or sell its house and become a renter, or default, and the region where it moves over the period:

$$V_t^{oL}(a, b_t, y_t) = \max \left\{ V_t^{oL,oL}, V_t^{oL,oH}, V_t^{oL,rL}, V_t^{oL,rH}, V^{oL,d} \right\} \tag{29}$$

Denote the resulting policy function for the discrete choice problem as $d_t^{oL} \in \{oL, oH, rL, rH, d\}$.

Inactive owner The value of staying a home owner in region L is given by the Bellman equation with fixed housing services $\overline{h}$,

$$V_t^{oL,oL}(a, b_t, y_t) = \max_{c_t, b_{t+1}} \frac{u\left(c_t, \overline{h}\right)^{1-\gamma}}{1-\gamma} + \Xi_L^o + \beta \left(p_a \mathbb{E}_t \left[V_{t+1}^{oL}(a+1, b_{t+1}, y_{t+1}) \right] + (1-p_a) U_{t+1} \right), \tag{30}$$

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

$$c_t + b_{t+1} + \delta P_{L,t}\overline{h} = y_t - T\left(y_t\right) + (1+\tilde{r}) b_t, \tag{31}$$

and the loan amortization constraint described earlier,

$$b_{t+1} \geq \min\left[\tilde{\theta} b_t, 0\right]. \tag{32}$$

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, $U_{t+1} = \frac{\psi((1+r^b)b_{t+1} + P_{L,t}\overline{h})^{1-\gamma}}{1-\gamma}$.

Mobile owner When selling its house and purchasing a house in the other region H, an owner incurs the moving cost m:

$$V_t^{oL,oH}(a, b_t, y_t) = \max_{c_t, b_{t+1}} \frac{u\left(c_t, \overline{h}\right)^{1-\gamma}}{1-\gamma} + \Xi_L^o - m + \beta \left(p_a \mathbb{E}_t \left[V_{t+1}^{oH}(a+1, b_{t+1}, y_{t+1}) \right] + (1-p_a) U_{t+1} \right) \tag{33}$$

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, In addition, there are sales transaction costs f_s and maintenance costs $\delta P_{t,L}\overline{h}$ on the house sold in region L,

$$c_t + F_m + P_{H,t}\overline{h}(1+f_m) + b_{t+1} = y_t - T(y_t) + (1+\tilde{r})b_t + (1-f_s-\delta)\,P_{L,t}\overline{h},$$
$$b_{t+1} \geq -\theta_{LTV,t}P_{H,t}\overline{h} \quad \text{and} \quad b_{t+1} \geq -\frac{\theta_{PTI,t}}{\left(1+r^b-\tilde{\theta}\right)}y_t. \tag{34}$$

Home seller 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 $\delta P_{L,t}\overline{h}$:

$$V_t^{oL,rL}(a,b_t,y_t) = \max_{c_t,b_{t+1}} \frac{u\left(c_t,\overline{h}\right)^{1-\gamma}}{1-\gamma} + \Xi_L^o + \beta\left(p_a\mathbb{E}_t\left[V_{t+1}^{rL}(a+1,b_{t+1},y_{t+1})\right] + (1-p_a)U_{t+1}\right), \tag{35}$$

subject to the budget and no-borrowing constraints

$$c_t + b_{t+1} = y_t - T(y_t) + (1+\tilde{r})b_t + (1-f_s-\delta)\,P_{t,L}\overline{h},$$
$$b_{t+1} \geq 0 \tag{36}$$

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

Mobile home seller The value of selling its house to move and become a renter in the other region H is identical the previous one, with the addition of the moving cost m.

Defaulting owner A defaulter does not repay its mortgage, incurs a utility penalty d and becomes a renter in the same region in the next period:

$$V_t^{oL,d}(a,b_t,y_t) = \max_{c_t,b_{t+1}} \frac{u\left(c_t,\overline{h}\right)^{1-\gamma}}{1-\gamma} + \Xi_L^o - d + \beta\left(p_a\mathbb{E}_t\left[V_{t+1}^{rL}(a+1,b_{t+1},y_{t+1})\right] + (1-p_a)U_{t+1}\right), \tag{37}$$

subject to the budget and no-borrowing constraints

$$c_t + b_{t+1} = y_t - T(y_t),$$
$$b_{t+1} \geq 0 \tag{38}$$

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

B.3 Welfare

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:[39]

$$V(s, S_p) = \frac{u((1+\omega(s))c(s,S_b),(1+\omega(s))h(s,S_b))^{1-\gamma}}{1-\gamma} + \Xi(s) + \beta\mathbb{E}\left[V(s', S_p)\,|s\right] \tag{39}$$

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

$$\omega(s) = \left(\frac{V(s,S_p) - V(s,S_b) + u_b}{u_b}\right)^{\frac{1}{1-\gamma}} - 1 \tag{40}$$

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. 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.[40]

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

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

[40] 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.

B.4 Numerical Solution

Steady state Fix the parameters $\overline{h}, \delta$ and ρ_j, ho_j^{sqft}, which are directly measured in the regional panel of Section 2. In steady state, the model is solved in three steps.

First, fix P_L^*, P_H^*, to exactly match the regional distribution of house prices in the data.

Second, vary rents R_L^*, R_H^* to target home ownership rates in the data, $ho_L^{hh}(\mathbf{P}^*, \mathbf{R}^*)$ and $ho_H^{hh}(\mathbf{P}^*, \mathbf{R}^*)$. Home ownership 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. For given local prices, home ownership rate are increasing in local rents. If migration rates are low, R_L and R_H can be separately chosen in regions L and H, otherwise they must be jointly solved for. Choose the amenity benefits ξ_j^r to match average rent levels, and benefits from owning ξ_j^o to match home ownership rates.

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 $\overline{I}_j$ in closed form:

$$\overline{I}_j = \frac{\delta \overline{h} ho_j^{hh} pop_j}{ho_j^{sqft} P_j^{\rho_j}}. \tag{41}$$

Given the new $\overline{I}_j$, go back to the first step and iterate until convergence.

Transition dynamics Households' value functions are subject to i.i.d. idiosyncratic taste shocks following a type I Extreme Value distribution, which cancel out in the aggregate. This is a classical assumption in the dynamic demand literature. 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 key to solve for the dynamics of the regional distribution of prices and rents in response to unanticipated shocks, without generating jumps in marker-clearing conditions.

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:

$$\tilde{V}^{rL}(a, b_t, y_t) = V^{rL}(a, b_t, y_t) + \tilde{\varepsilon}^{rL}(a, b_t, y_t) \tag{42}$$

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

(i) It smooths 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 regions). It smooths out policy and value functions, and makes them more monotonic with respect to prices when solving for them numerically. This allows to reduce the size of the state space and make the problem tractable. Without it, an extremely high number of grid points would be needed to avoid jumps in value functions over the transition. The expectation of the envelope value has a closed form, for instance for region L renters:

$$\mathbb{E}_{L,t}\left[V^r\right] = \mathbb{E}_{L,t}\left[\int \tilde{V}^r \mathbf{dF}\left(\tilde{\varepsilon}\right)\right] = \mathbb{E}_{L,t}\left[\log\left(\sum_{j=1}^{4} e^{\tilde{V}^{r,j}}\right)\right] \tag{43}$$

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

(ii) One obtains closed-form expressions 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:

$$\Pr\left(\tilde{V}^{r,j} = \tilde{V}^r\right) = \frac{e^{\tilde{V}^{r,j}}}{\sum_{j'=1}^{4} e^{\tilde{V}^{r,j'}}} \tag{44}$$

(iii) One can compute the dollar cost of policies in closed-form.

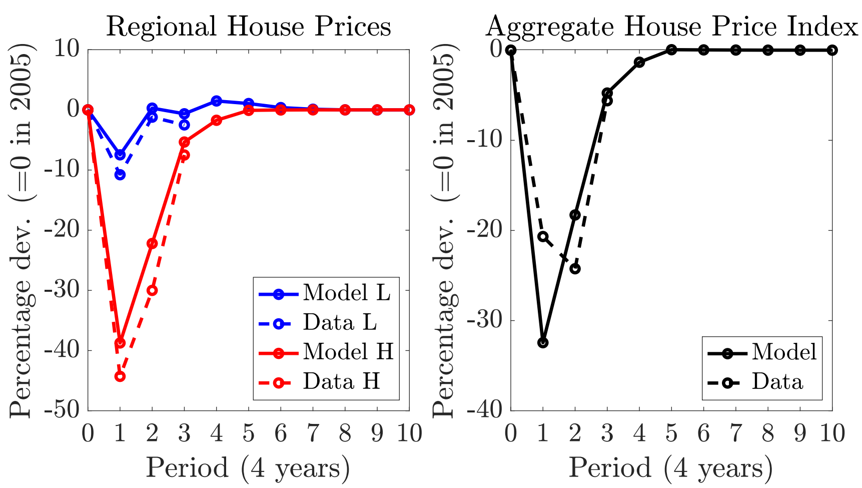
Computations The steady state takes 10 seconds to compute. The transition dynamics takes 15 minutes to compute, when parallelized on the NYU high-performance cluster using 20 cores with 28GB of memory each.

C Extended Model

In addition to the shocks in the baseline model, households' valuations of owner-occupied units $\left\{\Xi^o_{j,t}\right\}$ now also fall. They are chosen to match the residual decrease in house prices after accounting for income and credit shocks. They generate realistic increases in default rates in the aggregate and across regions. This shock is similar to the valuation shocks in Guren and McQuade (2020). The "double trigger" motive for default is the reason why households default in the model (e.g., Campbell and Cocco (2015)). It allows underwater borrowers in need of liquidity to smooth consumption, typically after a negative income shock.

As Figures 29 and 30 show, the resulting model matches the dynamics of house prices and leverage. As Figure 31 shows, the model qualitatively replicates the dynamics of credit risk in the data. The increase in default rates is short-lived. 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 leverage, hence the probability that new buyers default on their mortgages.

Figure 29: House prices responses in the model with valuation shocks

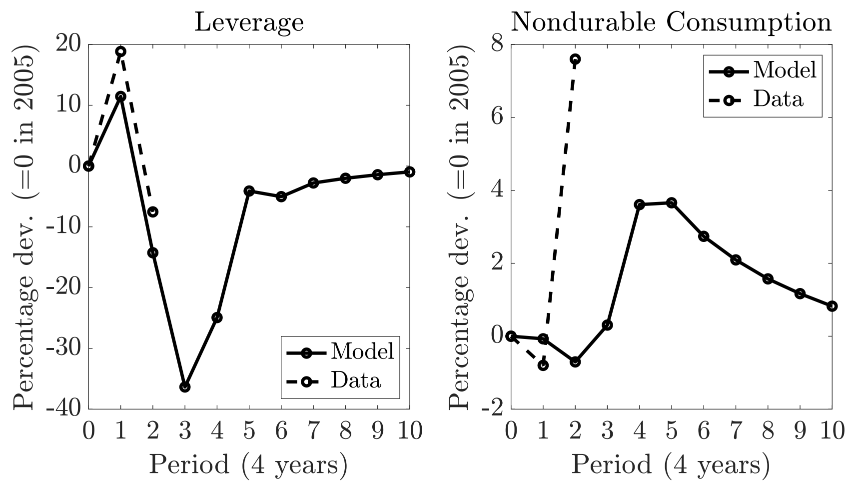


Notes: Low-price MSAs in blue, high-price MSAs in red. Data source: Zillow.

D Detailed Steady State Results

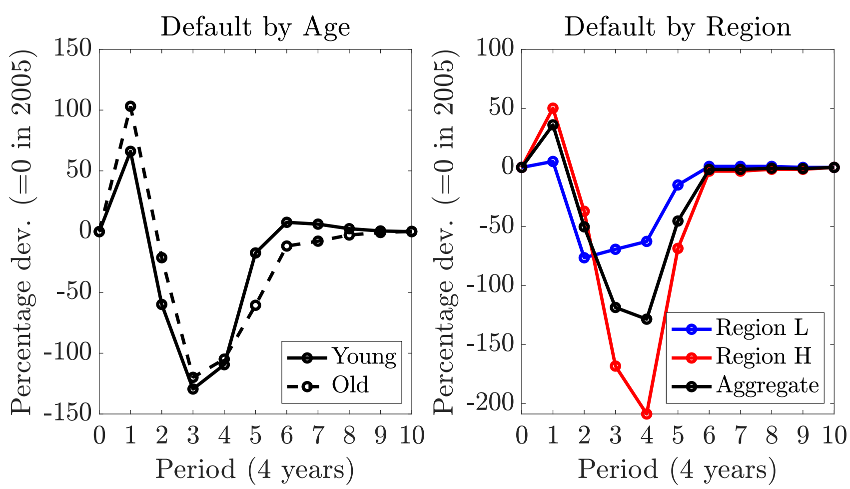
D.1 Aggregate Housing Market

Figure 30: Leverage and consumption response in the model with valuation shocks



Notes: Leverage is computed as total mortgage debt outstanding to total housing value. Real Personal Consumption Expenditures for Nondurable Goods (U.S. Bureau of Economic Analysis). Changes in percentage terms relative 2005.

Figure 31: Default rates by age and region group in the model with valuation shocks



Notes: default rate percentage changes from 2005. Left panel: for 25-44 (solid) and 45-85 year old households (dashed). Right panel: low-price MSAs in blue, high-price MSAs in red, aggregate in black.

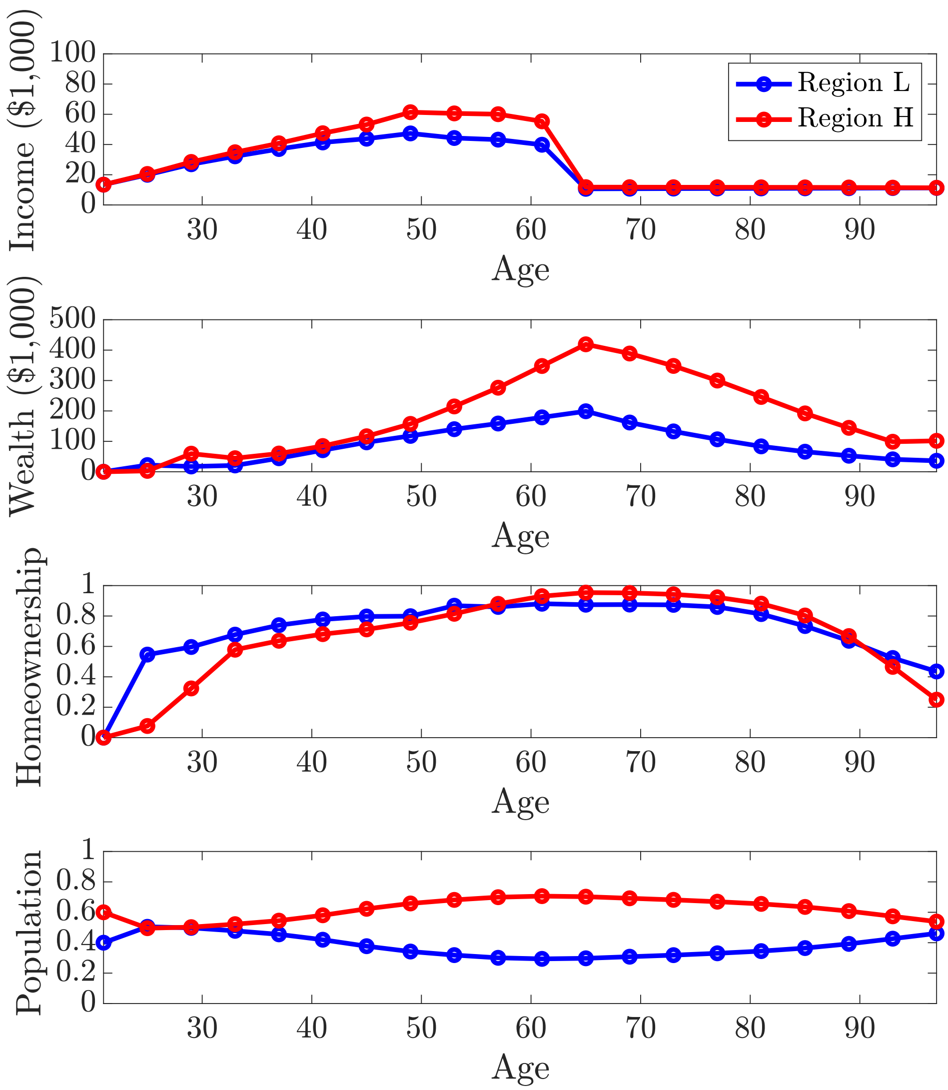
Table 12: Additional aggregate moments

Variable	Data	Model
Fraction homeowners with mortgage	0.66	0.57
Avg. size occupied/rented unit	1.50	1.78

Notes: Moments not targeted by the calibration. Source: Kaplan et al. (2020).

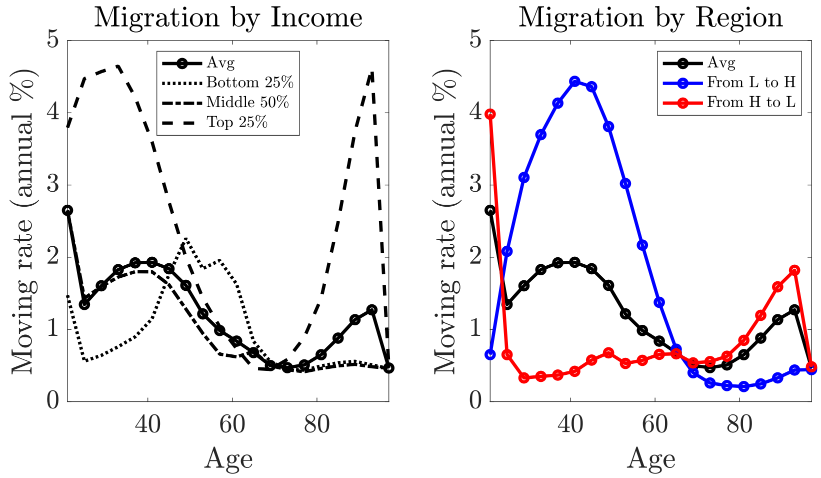
D.2 Life-Cycle

Figure 32: Life-cycle profiles of labor income, wealth, home ownership, and population shares



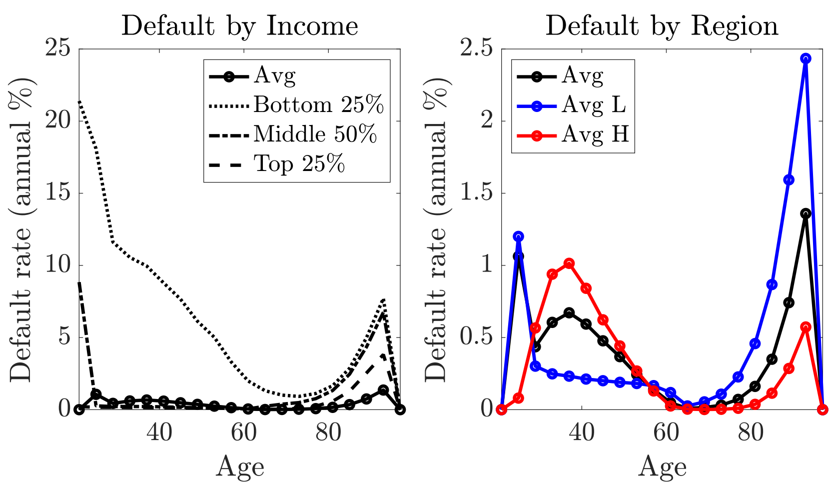
Notes: Household life-cycle profiles from 21 to 95 years old. Upper panel: gross annual labor income (including pensions) in thousands of 1999 dollars. Upper middle panel: wealth (including housing) in thousands of 1999 dollars. Lower middle panel: home ownership rate. Lower panel: regional population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

Figure 33: Life-cycle profiles of migrations by income and region group



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. Right panel: average (black), from low- to high-price MSAs (blue), from high- to low- price MSAs (red).

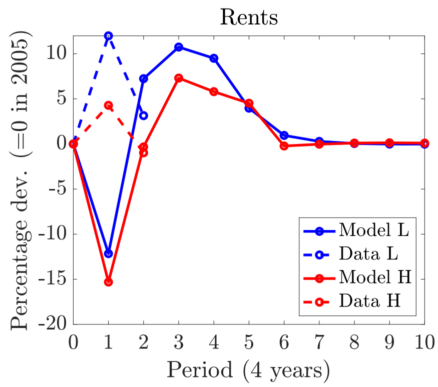
Figure 34: Life-cycle profiles of default by income and region group



Notes: Household life-cycle profiles of default 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, in low-price MSAs (blue), in high-price MSAs (red).

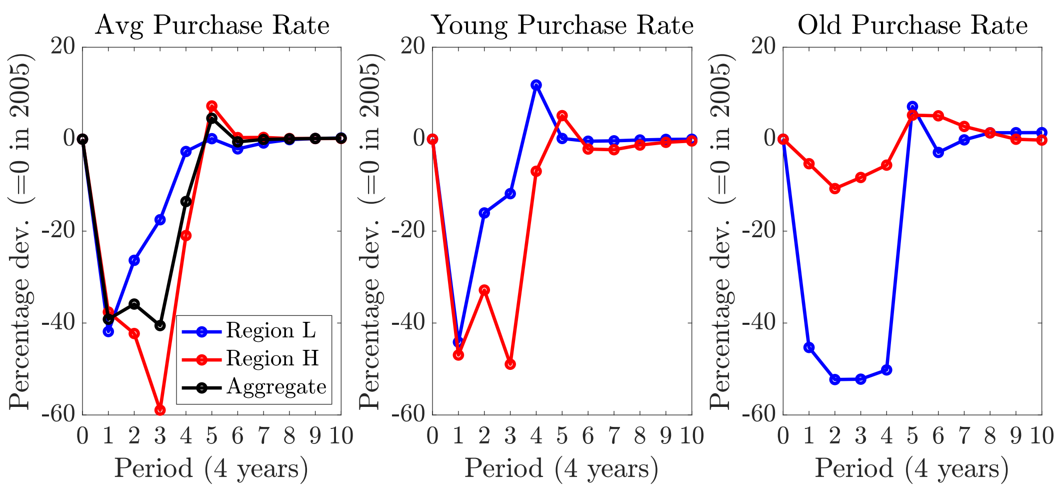
E Detailed Dynamic Results

Figure 35: Rent dynamics



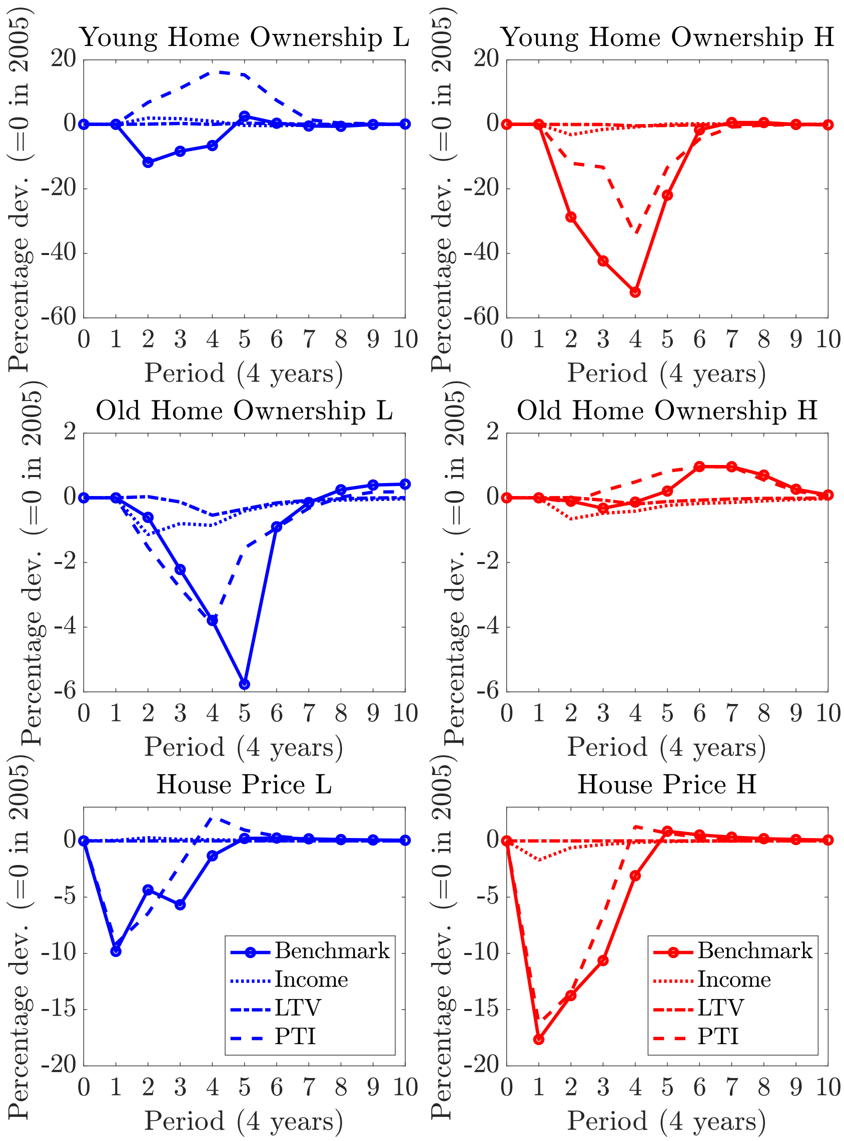
Notes: Average rents in the data (dashed lines) are measured as population-weighted averages of the Zillow Rental Indexes, and are linearly detrended to make them stationary. Low-price MSAs in blue, high-price MSAs in red.

Figure 36: Propensity to buy response to aggregate recession



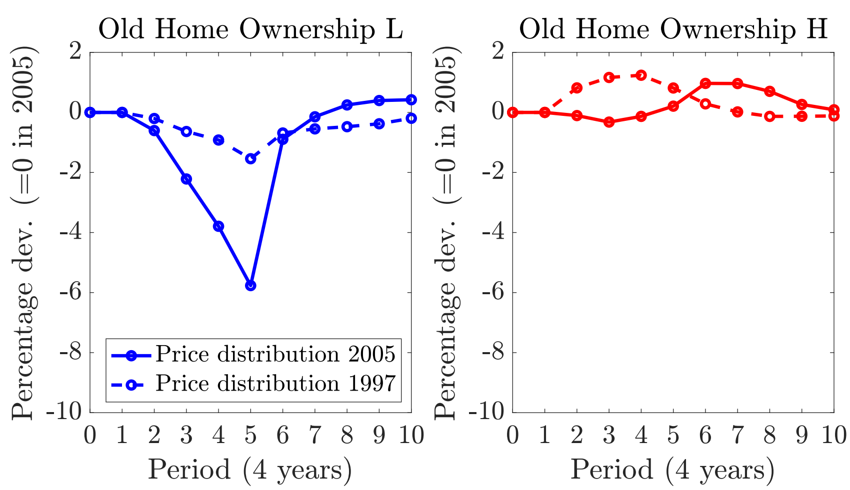
Notes: Renters' propensities to buy are measured as purchase rates, i.e. conditional probabilities to buy, for each region and age group. Purchase rate change for an average household (left panel), 25-44 year old households (middle), 45-85 year old households (right). Low-price MSAs in blue, high-price MSAs in red, economy average in black. Changes in percentage terms relative to 2005.

Figure 37: Shock contributions to home ownership and house price responses



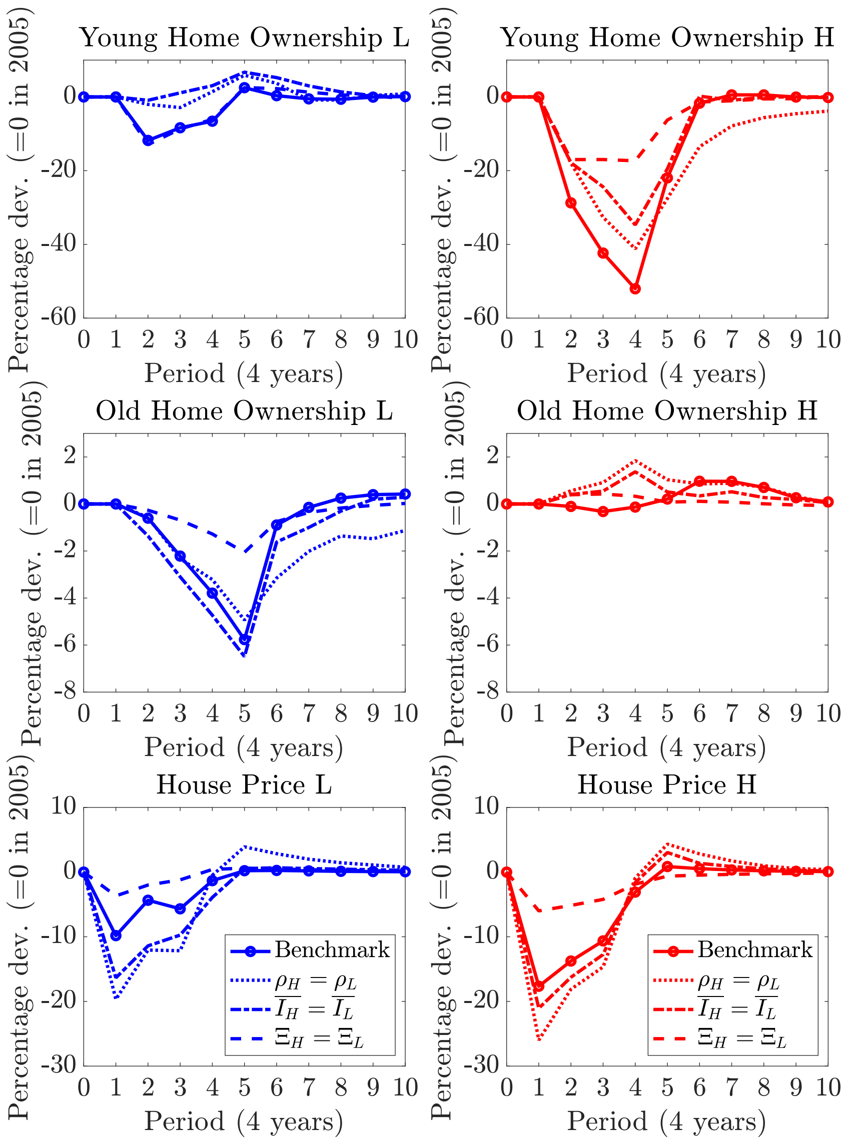
Notes: Low-price MSAs in blue, high-price MSAs in red.

Figure 38: Old home ownership response by region group under alternative house price distributions



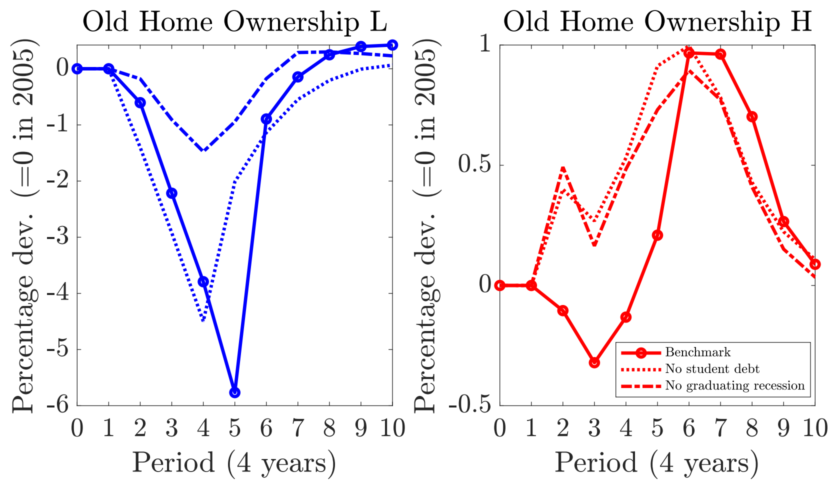
Notes: Low-price MSAs in blue, high-price MSAs in red.

Figure 39: Contributions of regional differences to home ownership and house price responses



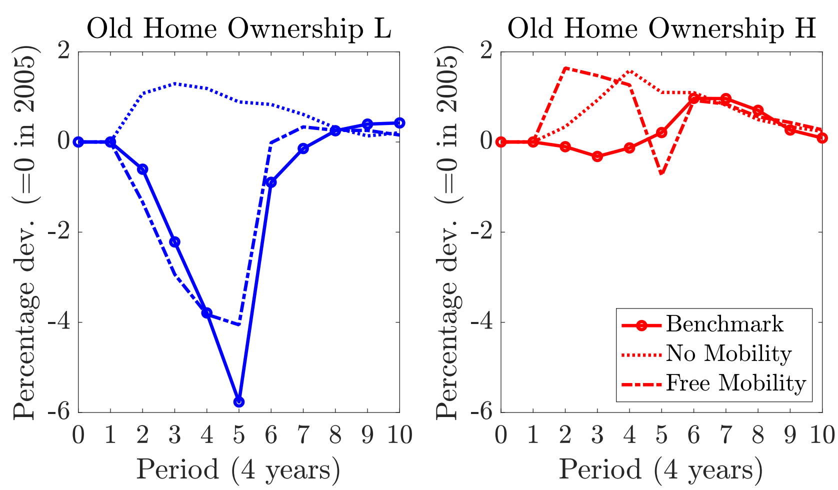
Notes: Low-price MSAs in blue, high-price MSAs in red.

Figure 40: Contributions of cohort differences to old home ownership response



Notes: Low-price MSAs in blue, high-price MSAs in red.

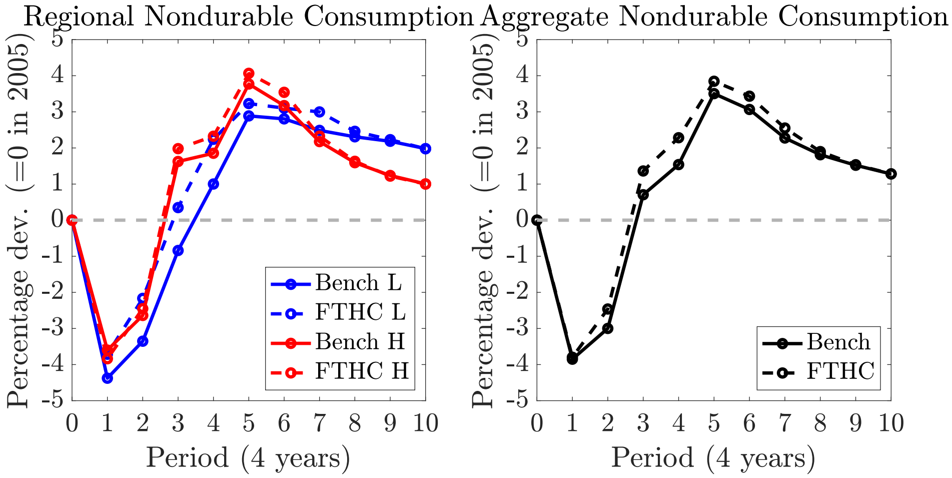
Figure 41: Effect of mobility on old home ownership response



Notes: Low-price MSAs in blue, high-price MSAs in red.

F Detailed Policy Results

Figure 42: Effect of the First-Time Homebuyer Credit on consumption



Notes: Low-price MSAs in blue, high-price MSAs in red. The solid lines represent benchmark responses without the policy. The dashed lines represent responses with the policy. In both cases the economy is subject to the same sequence of negative income and credit shocks as in the benchmark.