Unemployment and the US Housing Market during the Great Recession*

Job Market Paper

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This version: April 10, 2018
Latest version: http://www.stanford.edu/~pavelkr/jmp.pdf

Abstract

This paper evaluates the role of unemployment scarring and fear thereof for the recent U.S. housing bust. I study a quantitative lifecycle model of the housing market, which features an income process that is consistent with the large and long-lasting impact of unemployment on future earnings documented in recent empirical work. The model features exogenous moving shocks consistent with survey evidence which shows that many households move for reasons unrelated to their financial situation. These shocks reduce the selection into moving, thereby amplifying the quantitative importance of unemployment shocks and tighter credit conditions in the recent bust. The reason is that movers are more sensitive to labor market and credit conditions because they are younger, have lower wealth, and less secure jobs. Housing policies such as mortgage subsidies help stabilize prices and reduce foreclosures, even if only a small fraction of homeowners receive them.

*I am grateful to my advisors Martin Schneider, Monika Piazzesi, and Gregor Jarosch for their support and guidance. I am particularly thankful to Alina Arefeva, Adrien Auclert, Nick Bloom, John Y. Campbell, Vladimir Dashkeev, Bob Hall, Eran Hoffmann, Katya Kartashova, Patrick Kehoe, Pete Klenow, Pablo Kurlat, Kurt Mitman, Richard Rogerson, Alex Suzdaltsev, Yevgeniy Teryoshin, Christopher Tonetti, Alonso Villacorta, and to the seminar participants Stanford, UN Reno, Nazarbayev University, UT Dallas Naveen Jindal School of Management, Luxembourg School of Finance, Baruch College Zicklin School of Business, and the Federal Reserve Bank of Richmond for their comments and discussion. I gratefully acknowledge the financial support from the Stanford Institute for Economic Policy and Research as a B.F. Haley and E.S. Shaw Fellow. All errors are mine.

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1 Introduction

Housing wealth and mortgage debt account for over 3/4 of a typical US household's assets and liabilities, respectively (Kwak, 2009). Between 2007 and 2012, house prices fell by about 30%, and 10% of mortgages turned delinquent.[1] Households lost a sizable share of their wealth, and many defaulted on their mortgages. Why did this happen and which forces were the key quantitative culprits? This is the topic of an emerging quantitative literature but a consensus has yet to be reached. In particular, it is still an open question to which extent the spike in unemployment has contributed to the collapse of the housing market. As a consequence, how effective was the US mortgage policy?

In addressing these questions I pay particular attention to matching key empirical characteristics of movers: they are younger, have less secure jobs and are more credit constrained than an average household. This leads me to find that the most important forces behind the bust were tighter credit constraints on mortgages and the weak labor market. In turn, I find far smaller effects of declining house price expectations and of other credit conditions. The Home Affordable Modification Program helped avoid a much larger drop in house prices, but could have been more effective had more households applied.

In the model, individual households' consumption-savings and portfolio choice problems determine their demand for housing. House prices equate the demand with the observed housing supply for all house types. Households can borrow using mortgages, credit cards, and home equity lines of credit. They are credit constrained and can prepay or default on any loan. Their income process has empirically plausible consequences of unemployment, that have a large income effect on the housing demand. This paper is a quantitative study of the housing bust during the great recession that captures the available micro-empirical evidence on the consequences of job loss. Finally, both credit and labor market conditions, as well as house price expectations follow a two-stage boom-bust Markov process.

I quantify the model using the panel dimension of the 2007-9 Survey of Consumer Finances (SCF), several other surveys, and macro data. First, I start the model in 2007 SCF distribution of households and solve for the equilibrium given the observed stock of houses in 2007. In this exercise, I choose preference parameters to match the aggregates in the housing boom. The model closely captures the untargeted cross-sectional distribution of household savings, mortgage borrowing, homeownership, and the moving rate. Second, I fix the preference parameters and start the model in the 2009 distribution of households and stock of houses, solve for the new equilibrium and compare it to the one in 2007. The model

[1] Compared to 2007, the real median home value was 15% lower in 2009 and 31% lower in 2012, according to Zillow data deflated with CPI. For more details, see Figure 3 in Appendix.

produces a 25% decline in house prices and matches the delinquency rate on credit cards and mortgages which increased two-fold. In both exercises, I pick credit and labor parameters from external sources, so that they follow the observed changes in the data, while the housing bust is untargeted.

Houses are illiquid assets. They take time to sell and involve transaction costs.[2] Only 7% of houses trade in a year, while the turnover rate for stocks is above 100%.[3] Therefore, house buyers are a small subset of the population. Since house prices are determined by the Euler equations of the buyers, it is important to capture how movers may differ from the rest of the population.

In particular, more than 30% of movers report that they move for family reasons. For example, they get married, have children, or move in with the relatives (for a survey, see Ihrke (2014)). This fact is ignored in existing quantitative work on the housing bust where a move always reflects an optimal response to the current economic conditions of the household. Allowing for random moving shocks distributed as in the data has two important implications for a quantitative model of the housing bust. First, there is always a subset of young movers who are just about to buy a house and are sensitive to labor and credit conditions.[4] Second, even if a mover can afford a house at current price, he/she may be particularly concerned with future credit and labor market conditions because of a potential need to move once more in the future. Both these features are likely to give rise to a more severe housing bust during downturn.

This paper emphasizes the role of moving for reasons other than changes in income, credit or housing market conditions. Households move when they find it optimal to move, or because they are hit by an exogenous moving shock. The distribution of moving shocks is age-specific and differs for homeowners and renters. I quantify this distribution using the survey about moving reasons in the SCF2007-9 and the U.S. Census data. As a result, the model matches moving rates by age, including those moves that arise endogenously (not from a moving shock). Moving shocks do not change over the boom-bust episode, but the presence of moving shocks sharply amplifies the effects of credit and labor conditions.

The model matches the features of the micro data. Most young agents do not own houses, because they have low income and low financial wealth. The transition to homeownership happens mostly at ages 25-35, but later for lower income households because it takes more

[2]It was taking up to 50 weeks to sell a house during the housing bust (Garriga and Hedlund (2016)). The realtor's fee, taxes and other costs may sum up to 6% of house value (Piazzesi and Schneider (2016)).

[3]The turnover rate is the ratio of sales to the stock of the asset. The difference was even larger during the housing bust: most of the time between 2007 and 2011 the turnover rate was above 200% for stocks and below 6% for houses.

[4]The young move much more than the old: over 2007-2009, the average moving rate was greater than 25% for 21-35 year old, but less than 8% for 45+. For a survey, see Benetsky et al. (2015).

time for them to save for the downpayment. Those who lose their jobs do not necessarily sell their houses: instead, they use home equity lines of credit to borrow against their houses. Households who cannot afford mortgage payments do not always default: if the value of the house is larger than the outstanding mortgage, they just sell the house and repay the mortgage to avoid the cost of default.

To compare the housing boom with the subsequent bust, I solve for the equilibrium in the model for two years, 2007 and 2009. Starting from the initial conditions in that year, I compute equilibrium prices and the distribution of household choices. Households in the model solve the full dynamic problem given their conditional expectations about future income and house prices. I measure house price growth expectations directly using survey evidence. The set of parameters is the same across the two exercises, but the 2007 exercise starts the economy in a good aggregate state ("boom"), while the 2009 exercise starts in a bad state ("bust"). The credit and labor market conditions depend on these two aggregate states. In the bust state, credit constraints tighten and unemployment is higher. Households form their expectations conditional on the aggregate state of the Markov process, so that equilibrium choices and prices depend on the conditions in both states.

The equilibrium outcomes for 2007 and 2009 differ for two reasons: (1) the different initial aggregate state (boom versus bust) and (2) a different initial distribution of household characteristics, measured from the 2007 and 2009 SCF, respectively. The first reason explains over 90% of the differences in outcomes, which I further decompose into the effects of different subsets of parameters to study the relative importance of different mechanisms and their interactions. The model attributes 12-17% drop in house prices to tighter borrowing limits on mortgages, 9-11% to a weak labor market, and 3-6% to lower house price growth expectations, while the tighter conditions for Helocs and credit cards each explain 2-3%. Removing the mortgage subsidy drops house prices by extra 9-10%.

This paper builds on a large literature which studies quantitative housing models to understand the forces behind households' decisions and house price fluctuations (such as transaction costs, collateral constraints, and life cycle patterns).[5] Recent papers use micro-data to investigate the mechanisms of the housing bust. I contribute along two dimensions: by evaluating the role of unemployment (and fear thereof) and by matching the empirical characteristics of movers. I show in the context of my model that both features are essential to understanding the housing bust.

Garriga and Hedlund (2016) study a search model of the housing market with infinitely lived households and perfect foresight, and match the fluctuations in the time on market (the time it takes to sell a house). They also find large effects of income and credit on

[5]For a survey of this literature, see Piazzesi and Schneider (2016).

house prices, but for different reasons. First, the income process features left tail risk which captures unemployment. The second reason is search frictions: it takes longer to sell a house in a housing bust. In other words, households cannot sell houses exactly when they want. As a result, households cannot entirely avoid trading in adverse conditions, and are more concerned about them.[6]

Greenwald (2016) focuses on the interaction of payment-to-income and downpayment constraints on mortgages. He shows that payment-to-income constraints amplify the effect of interest rates on house prices and have a large effect on their own, as households switch between which of the two constraints is binding. The same effects are present in my paper, and payment-to-income constraints also play a large role in the bust.

Kaplan, Mitman, and Violante (2017) find virtually no effect of credit constraints and income shocks on house prices, and attribute the decline in house prices to a residual term, interpreted as expectations. I document that, indeed, credit constraints and labor income shocks matter much less in a model without moving shocks and unemployment scars. First, in absence of moving shocks households worry less about credit constraints, because they are applied only at loan origination, and it is possible to stick to one loan forever. Second, in absence of unemployment scars, income shocks matter less, because they have smaller effect on lifetime income.

This paper is also related to the mortgage policy discussion. Mitman (2016) studies a quantitative model with exogenous house prices to evaluate the effects of two policies (BAPCPA and HARP). I complement this paper by focusing on another policy (HAMP) and studying its impact on house prices. In a theoretical study, Eberly and Krishnamurthy (2014) argue that a policy that focuses on lower income households and subsidizes annual payment (instead of writing off principal) is effective in reducing defaults. HAMP is an example of such a policy, and I confirm quantitatively that it has a large effect on defaults.

Households receive a labor income process in this paper that builds on the findings in the empirical labor literature about the consequences of unemployment as documented by Jacobson, LaLonde, and Sullivan (1993), Hall (1995), and Stevens (1997). Davis and von Wachter (2011) find that losing a job has a large and long lasting impact on future earnings, which is bigger for jobs lost during recessions as compared to expansions. They also present survey evidence suggesting that households are aware about that. My modeling of income process is similar to Jarosch (2015) who proposes a model that matches the consequences of job loss in German data and is consistent with Davis and von Wachter (2011) estimates for

[6] Branch, Petrosky-Nadeau, and Rocheteau (2016) use macro-data and study a search model of the labor market in which a fraction of households do not have access to unsecured credit and can borrow only through home equity lines of credit. The collateral value of a house is therefore large and sensitive to heloc borrowing limit, which makes this limit important for house prices.

the US data.

The rest of the paper is organized as follows. Section 2 describes the model, section 3 explains the quantitative exercise, section 4 presents the results, and section 5 concludes.

2 Model

This section will first describe the model and its solution. Then I will motivate the assumptions and discuss their relationship to the literature.

2.1 Setup

2.1.1 Goods and Preferences

Time is discrete, the frequency is annual. The economy is populated with a continuum of people, each works for T years and is retired for R years. They discount future at a rate β, have CRRA preferences over time and risk, and Cobb-Douglas utility over consumption C and housing services H.

$$V_{age}(\Omega) = \mathbb{E} \sum_{t=age}^{L+R} \beta^{t-age} \frac{U_t^{1-\gamma} - 1}{1-\gamma} \tag{1}$$

$$U_t = C_t^{1-\alpha} H_t^{\alpha} \tag{2}$$

where the vector Ω contains all the state variables that are relevant to the household (such as income, unemployment, and balance sheet variables). Households make decisions for the first T years while they are in the labor force. Consumption and housing services for the last R years are constant and determined at the moment of retirement.

While consumption is continuous, housing services can take 3 levels: $H \in \{1, H_1, H_2\}$, where $1 < H_1 < H_2$. The lowest level, normalized to 1, corresponds *rental apartments*. The other two values can be achieved only through the ownership of *houses*. Households cannot own more than one house. Those who do not own a house have to rent an apartment.

Apartments are elastically supplied for rent at an exogenous rate p. The supply of each type of houses is fixed. The house prices P_1 and P_2 are determined in equilibrium.

People move in order to change housing type or as a result of a *moving shock*. Movers incur a proportional utility cost, so that the new utility becomes $(1 - \tau_{move})U_t$. Moving shocks are idiosyncratic, independent across households and time, and happen with different age-specific probabilities for renters and homeowners. If a shock hits a homeowner, they have to sell their house, and can buy a new house of any size or rent an apartment.

2.1.2 Assets and Liabilities

Households can own two types of assets: *houses* and *deposits*. *Deposits* pay a risk-free rate r_d. *Houses* provide housing services as explained above and require a proportional cost t_m that includes property tax and maintenance. The illiquidity of houses is reflected in a proportional transaction cost t paid by the seller.

There are three ways to borrow: *credit cards, mortgages*, and *home equity lines of credit (HELOCs)*. The APR on *credit cards* is $r_c > r_d$, the credit limit is $\bar{B} \times Y$, where Y is individual income (before the transitory shock is realized, as explained below). Households can decide to default on credit card debt at a proportional utility cost τ_c, i.e. the utility becomes $(1 - \tau_c)U_t$.

Mortgages are long-term contracts with prepayment and default options. When a household buys a house at a price P, it pays a fixed origination cost F_m, makes a downpayment $d \times P$ and takes a mortgage $(1 - d) \times P$. Mortgages are prepayable anytime at no cost, but only in full (partial prepayment is not allowed). The interest rate is r_m and satisfies $r_d < r_m < r_c$. The annual payment for an initial balance D is $(r_m + \delta)D$, and after the payment is made, the remaining balance becomes $(1 - \delta)D$. The borrowing limit on mortgages is defined in terms of payment to income ratio, that cannot exceed $\bar{D}$. Households can default on mortgages at a proportional utility cost τ_d (the utility becomes $(1 - \tau_d)U_t$). Default on a mortgage initiates a foreclosure. In case of a foreclosure, the household receives $max\{0, (1 - t - t_f)P - (1 + r_m)D\}$, i.e. there is no recourse but there is a proportional cost of foreclosure t_f.

Homeowners can use their houses as collateral to open *home equity lines of credit*. HELOCs have the interest rate r_h, and require a fixed cost FC_{heloc} per year. The borrowing limit is $(1 - \nu)P - D$. Households can default on helocs, but it initiates a default on the underlying mortgage.

The *mortgage subsidy* equal to a share r_{sub} of annual mortgage payment is available to the low income households (explained below) with the mortgage payment to income ratio between $\bar{D}^L_{sub}$ and $\bar{D}^H_{sub}$. This policy is similar to the Home Affordable Modification Program (HAMP) introduced in 2009.

2.1.3 Income process

Households face idiosyncratic labor income risk. Individual income is determined by *human capital*, *employment*, and the realization of a *transitory shock*.

$$Y_{i,t} = W_{i,t} \times z^{U_{i,t}} \times e^{\theta_{i,t}} \tag{3}$$

where $W_{i,t}$ is the human capital of person i in year t, $z \in (0, 1)$ is the unemployment benefit as a fraction of wage, $U_{i,t} \in \{0, 1\}$ is the indicator of the person i being unemployed in year t, and $\theta_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma_\theta)$ is a transitory shock.

While $\theta_{i,t}$ drives transitory fluctuations of labor income, its permanent component is captured by the interaction of employment and human capital.

Figure 1 summarizes the income process. There are three levels of human capital: W_L, W_M, and W_H. At each level, human capital follows a deterministic life-cycle path. These levels capture a job ladder. Over time, people can randomly move up or down the ladder, depending on their employment history. If human capital is W_L or W_M and the household is *Employed*, there is a probability p_{up} to go one step up. If human capital is W_M or W_H and the household is *Unemployed*, there is a probability p_{down} to move one step down. This simple Markov process captures both the accumulation of human capital while being employed, and the long-term consequences of losing a job (sometimes referred to as *unemployment scar*).

The *Employed* face a risk of losing a job, that is given by job-specific separation probabilities $s_1 > s_2 > s_3$, with higher probability corresponding to lower levels of human capital. The ordering captures the positive correlation of job security and wage.

The *Unemployed* search for jobs constantly and at no cost. The job finding rate can take two values: $f_H < f_L$. Those who have low job finding rate f_L are referred to as *long-term unemployed*. When people lose jobs, they initially have high job finding rate but can switch to low rate with probability p_{LTU} every period while they are unemployed. The low rate is an absorbing state; unless unemployed workers find a job, they always have a low job finding rate. This feature of the model accounts for the heterogeneity within the unemployed and for the additional left tail labor income risk.

2.1.4 Business cycle

The business cycle is driven by a two-state Markov process. The states are called *Boom* and *Bust*, and the transition matrix is parameterized by the two probabilities: $P_{Boom \to Bust}$ and $P_{Bust \to Boom}$.

The following parameters differ across those states:

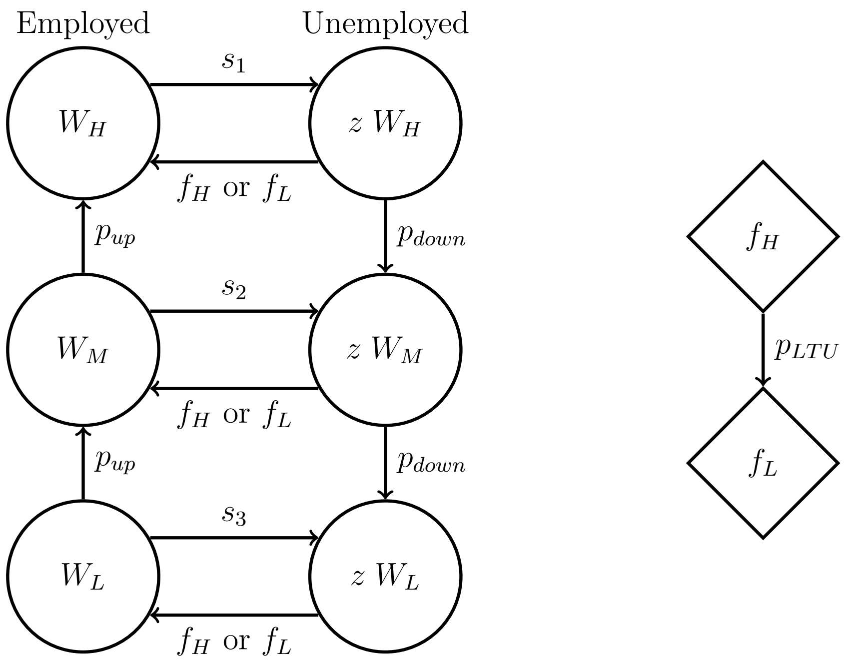
Labor: job finding rates f_H and f_L, risk of long-term unemployment p_{LTU}, unemployment replacement rate z

Finance: interest rates (r_d, r_m, r_h, r_c), borrowing limits (credit cards $\bar{B}$, mortgages $\bar{D}$, home equity lines of credit ν), mortgage downpayment d and amortization δ

Housing: housing transaction cost t, house price expectations (explained below)

Other parameters: existence of mortgage subsidy (it is present during the *Bust* only)

FIGURE 1: Income process.



Note: Left panel shows the Markov process for income. Lifecycle profile and transitory shocks are omitted for clarity. Right panel shows the Markov process for job finding rate of an unemployed. This diagram differs from a standard diagram for a Markov process in two ways. First, the recursive links are not shown, e.g. in the right panel the probability to stay at f_H is $(1 - p_{LTU})$. Second, if a node has two outgoing links, the corresponding events are independent (as compared to mutually exclusive in a standard diagram). E.g. for low income Employed (bottom left corner of Left panel) the probability to lose a job is s_3 and the probability to go up the ladder is p_{up}. This implies that the probability to keep the job and go up the ladder (i.e. go to the middle left node) is $(1 - s_3)p_{up}$, while the diagram shows p_{up} attached to the corresponding link. Similarly, it is possible to go up the ladder and lose the job simultaneously (i.e. go to the middle right node), but the link is not shown.

2.1.5 House price expectations

According to the survey data, households' expectations of house price growth are too optimistic and not sensitive to the observables as compared to econometrician's expectations (see e.g. Case, Shiller, and Thompson (2012)). The housing literature has documented that expectations are important for house price dynamics.[7] Therefore, I pay particular attention to matching the dynamics of expectations over the housing bust.

Four parameters drive expectations: two per each state (Boom and Bust). The first one, g_{stay} is the growth rate of house prices if the economy stays in the current state (I assume the expected growth rates of P_1 and P_2 are the same). The second one, g_{switch} is the growth rate of house prices if the economy switches to the other aggregate state. This way g_{stay} reflects gradual changes in house prices when the economy stays in one state, while g_{switch} captures sharp changes in transition between states.

Specifically, if the current aggregate state $Cycle_t = Boom$ and the current prices are $P_{1,t}$ and $P_{2,t}$, then prices tomorrow as functions of the aggregate state tomorrow are

$$P_{i,t+1} = \begin{cases} (1+g^{Boom}_{stay})P_{i,t} & \text{if } Cycle_{t+1} = Boom \\ (1+g^{Boom}_{switch})P_{i,t} & \text{if } Cycle_{t+1} = Bust \end{cases} \qquad i = 1,2 \tag{4}$$

Therefore, the distribution of prices tomorrow is (replace the if statements with probabilities)

$$P_{i,t+1} = \begin{cases} (1+g^{Boom}_{stay})P_{i,t} & \text{with prob. } 1 - P_{Boom\to Bust} \\ (1+g^{Boom}_{switch})P_{i,t} & \text{with prob. } P_{Boom\to Bust} \end{cases} \qquad i = 1,2 \tag{5}$$

Define the mean expected growth rate $\bar{g}^{Boom} = (1 - P_{Boom\to Bust})g^{Boom}_{stay} + P_{Boom\to Bust}g^{Boom}_{switch}$. Then the mean expected prices are $E_t P_{i,t+1} = (1+\bar{g}^{Boom})P_{i,t},\ i = 1,2$.

Similarly, the mean expected growth rate in the Bust is $\bar{g}^{Bust} = (1 - P_{Bust\to Boom})g^{Bust}_{stay} + P_{Bust\to Boom}g^{Bust}_{switch}$

2.1.6 Timing

In each year, the sequence of events is as follows.

1. The aggregate shock is realized

[7] Landvoigt, Piazzesi, and Schneider (2015) show that matching the survey expectations is important to explain the housing boom. Survey expectations were optimistic during the boom, that is necessary for the model to match the data. In particular, expectations in 2005 cannot be pessimistic. Among the bust papers, in Branch, Petrosky-Nadeau, and Rocheteau (2016) switching from perfect foresight of house prices to adaptive learning is necessary for the model to fit the magnitude of the housing bust. In Kaplan, Mitman, and Violante (2017) a shock to perceived probability of a shift to a state with high utility from housing is the main driver of the housing bust.

2. Moving shocks are realized

3. Households make decisions, house prices are determined, consumption happens

4. Transitory shocks to income are realized, transition across income groups, job separation, and job search happen, and long term unemployment shocks are realized. These determine the cash on hand, the distribution of people across income groups, the employment and long-term unemployment for the next period.

2.1.7 Equilibrium

The model is a small open economy for everything except houses. It takes interest rates and rental rate as given. The equilibrium is a set of individual decision rules as functions of individual state Ω, and the prices P_1 and P_2 as functions of the aggregate state (boom-bust) such that every household solves its dynamic problem and the markets for both types of houses clear.

2.2 Solution

2.2.1 State Space

Each household's decisions today depend on their individual characteristics, on the aggregate state of the economy (Boom or Bust), as well as on the distribution of individual characteristics across all the households, that is infeasibly large. To overcome this complexity I note that individual decisions depend on this distribution only through prices P_1 and P_2. The current prices are observable, and I add them to the household's state space. The households still have to predict the future prices, but given the structure of expectations, all the future prices are known functions of the current prices and the aggregate state.

This approach is not an approximation, but it is a full solution. It is possible because of the way the expectations are modeled. It is also convenient as it allows to express housing demand as function of prices that would be not possible it they were not a part of the state space.

Household's *state vector* Ω is composed of 11 variables. The aggregate variables are house prices $P_1 > 0$ and $P_2 > 0$ (both continuous), and the business cycle state $Cycle \in \{Boom, Bust\}$. The individual characteristics are age $A \in \{1, 2, ..., \bar{L}\}$, employment $L \in$ {employed, unemployed, long term unemployed}, the step on the job ladder $W \in \{W_L, W_M, W_H\}$, the realization of the moving shock $M \in \{0, 1\}$, the knowledge about the subsidy $S \in \{0, 1\}$, and the balance sheet. In turn, the balance sheet consists of a house $H \in \{0, 1, 2\}$, mortgage balance $D \geq 0$ (continuous), and non-housing networth B (continuous). Heloc balance is included in B and is not a separate variable, because it is short term credit, and households decide on it every period.

Household's *choice vector* ζ consists of 7 variables. Households choose consumption $C > 0$ (continuous), housing for the next year $H' \in \{0, 1, 2\}$, and make financial decisions. They decide on the non-housing networth B' (continuous), including heloc balance $heloc \geq 0$ (continuous). They also can prepay or default on a mortgage, and default on a credit card and heloc. Default on mortgage and heloc is one decision.

Renters have fewer state and choice variables as compared to homeowners: they do not have mortgage debt and do not make choices about heloc borrowing or mortgage prepayment and default.

2.2.2 Budget constraint of a renter

The income of a renter i is

$$Y_i = W_i(Age_i)e^{\theta_i}z^{U_i}, \tag{6}$$

where $U_i = 1$ if the renter is unemployed, and $U_i = 0$ otherwise.

The budget constraint in recursive notation is

$$(1 + r_i)B_i + Y_i - C_i - p - (dP'_i + F_m) \times \mathbb{1}_{H'>0} \geq -\bar{B}\ W_i(Age_i)z^{U_i}, \tag{7}$$

where the interest rate $r_i = r_d$ if $B \geq 0$ and $r_i = r_c$ otherwise. The renter receives interest on the deposit or pays interest on the credit card balance, pays for consumption and for the rental apartment. If he decides to buy a house at a price $P'_i \in \{P_1, P_2\}$, he makes a downpayment dP'_i and takes a mortgage $(1 - d)P'_i$ if it satisfies the payment-to-income constraint.

$$D' = (1 - d)P'_i \times \mathbb{1}_{H'>0} \tag{8}$$

The constraint implies that the credit limit is proportional to income, ignoring temporary shock[8].

$$\frac{(r_m + \delta)\big[(1 - d)P'_i - B'_+\big]}{W_i(Age_i)z^{U_i}} \leq \bar{D} \tag{9}$$

He cannot buy a house for cash only, but he can prepay the mortgage in full the next year if he wants[9]. Besides monetary cost, he pays a utility cost of moving.

[8] I ignore temporary shock for two reasons: (1) to simplify the computation, (2) banks may consider longer term income history and partially average away temporary fluctuations in income

[9] This assumption simplifies the computation, and it is not very restrictive as very few households can afford buying a house for cash. To make sure it does not have sizable effect, I modify the payment-to-income constraint by subtracting the positive financial networth $B'_+ = \max\{B', 0\}$ – so that those who can prepay a part of mortgage right away are less constrained by income.

If the renter decides to default on the credit card debt, then $B' = 0$, but he still has to respect the same credit limit right before he defaults (this rules out infinite consumption). It is not possible to simultaneously default and buy a house.

Though moving shock does not directly enter renter's budget constraint, it may change his demand for housing via two channels. First, a renter understands that if he buys a house today, he is likely to sell it later (if the shock hits him in future). This makes his housing demand lower. Second, when a renter is already moving because of the shock ($M = 1$ today), it is a good time to buy a house, because he has to experience the utility cost of moving anyway.

2.2.3 Budget constraint of a homeowner

Consider a homeowner i who decides not to prepay or default on her mortgage in the current year. Her income is $Y_i = W_i(Age_i)e^{\theta_i} z^{U_i}$. Her budget constraint is more complicated than the one of the renter as she has more decisions to make and may receive mortgage subsidy. Define the next period financial networth before mortgage payments and housing transactions but including maintenance costs as $\tilde{B}' = (1 + r_i)B_i + Y_i - C_i - t_{\text{maint}}P_i$. Then

$$B' = \begin{cases} \tilde{B}' - (r_m + \delta)D_i(1 - s_i r_{sub}), & \text{if } H' = H,\ M = 0,\ heloc = 0 \\ \tilde{B}' - (r_m + \delta)D_i(1 - s_i r_{sub}) - FC_{heloc}, & \text{if } H' = H,\ M = 0,\ heloc = 1 \\ \tilde{B}' - (r_m + 1)D_i + (1 - t)P_i, & \text{if } H' = 0 \\ \tilde{B}' - (r_m + 1)D_i + (1 - t)P_i - dP_i' - F_m, & \text{if } H' > 0,\ H' \neq H \\ \tilde{B}' - (r_m + 1)D_i + (1 - t)P_i - dP_i - F_m, & \text{if } H' = H,\ M = 1 \end{cases} \tag{10}$$

The constraint is $B' \geq -\bar{B}\ W_i(Age_i)z^{U_i}$, and the owner can default on the credit card.

$$D' = \begin{cases} (1 - \delta)D_i, & \text{if } H' = H,\ M = 0 \\ 0, & \text{if } H' = 0 \\ (1 - d)P_i', & \text{if } H' > 0,\ H' \neq H,\ \frac{(r_m+\delta)\left[(1-d)P_i' - B_+'\right]}{W_i(Age_i)} \leq \bar{D} \\ (1 - d)P_i, & \text{if } H' = H,\ M = 1,\ \frac{(r_m+\delta)\left[(1-d)P_i - B_+'\right]}{W_i(Age_i)} \leq \bar{D} \end{cases} \tag{11}$$

$$r_i = \begin{cases} r_d, & \text{if } B \geq 0 \\ r_c, & \text{if } B < 0,\ heloc = 0 \\ r_h, & \text{if } B < 0,\ heloc = 1,\ -B + D \leq \nu P_i,\ H' = H,\ M = 0 \\ \bar{r_i}, & \text{if } B < 0,\ heloc = 1,\ -B + D > \nu P_i,\ H' = H,\ M = 0 \end{cases} \tag{12}$$

where $\bar{r_i} = \frac{\nu P_i - D}{-B} r_h + (1 - \frac{\nu P_i - D}{-B}) r_c$ is the effective average interest rate when the household hits the HELOC borrowing limit and puts the rest of the debt on the credit card balance. Lines 1 and 2 of the equation for B' and line 1 of the equation for D' stand for the case when the owner keeps the house. This implies that she does not have to move for reasons coming from moving shock ($M = 0$). In this case, she pays the maintenance cost (that includes property tax) $t_{\text{maint}} P_i$ and makes an annual payment on the mortgage $(r_m + \delta) D_i (1 - s_i r_{sub})$, where $s_i \in \{0, 1\}$ indicates if she receives a subsidy equal to share r_{sub} of the annual payment.

She receives the subsidy if

– she is aware it is available: $S = 1$

– she is eligible: $\frac{(r_m+\delta)D_i}{W_i(Age_i) z^{U_i}} \geq \bar{D}^L_{sub}$, $\frac{(r_m+\delta)D_i}{W_i(Age_i)} \leq \bar{D}^H_{sub}$, and $W_i \in \{W_L, W_M\}$

The lack of z^{U_i} in $\frac{(r_m+\delta)D_i}{W_i(Age_i)} \leq \bar{D}^H_{sub}$ widens the eligibility range for payment-to-income ratio by including more unemployed (in 2009 more than half of HAMP participants report loss of income as the main reason they applied).[10]

Lines 2 and 3 in the equations for B' and D' respectively represent the case when an owner decides to sell the house and become a renter. In this case she pays the balance $(r_m + 1) D_i$ in full but receives the proceeds $(1 - t) P_i$ that account for the transaction cost of selling a house.

The last two lines are for the cases when an owner sells one house and buys another one. This is necessary if she wants to upsize or downsize ($H' > 0,\ H' \neq H$) or if she moves for other reasons and buys the house of the same size. In both cases she sells the old house, repays the old mortgage, then buys a new house and takes a new mortgage. Taking a new mortgage requires a downpayment and is subject to payment-to-income constraint.[11]

Finally, if an owner does not move, she can use home equity line of credit. This is a short-term contract, so she decides on it every period (that is why heloc balance is not a state variable). Heloc rate is lower than the credit card rate so if she opens a heloc, she transfers to it as much credit card balance as possible given the credit limit on heloc. Line 3 of equation 12 shows the case when the whole credit card balance is below the heloc limit. Line 4 shows the other case, for which I calculate an average interest rate given heloc use is at max.

If a homeowner decides to prepay the mortgage, only the first lines in the formulas for B' and D' would change to

[10] For more details, see HAMP performance report, December 2009.

[11] Here it is important to have positive networth B_+ in the payment-to-income constraint, because the owner is likely to have large networth after selling the old house.

$$B' = \begin{cases} \tilde{B}' - (r_m + 1)D_i, & \text{if } H' = H,\ M = 0,\ heloc = 0 \\ \tilde{B}' - (r_m + 1)D_i - FC_{heloc}, & \text{if } H' = H,\ M = 0,\ heloc = 1 \end{cases} \tag{13}$$

$$D' = 0,\ \text{if } H' = H,\ M = 0 \tag{14}$$

If instead she decides to default on the mortgage, she will have no mortgage debt ($D' = 0$), will have to rent for the next year, and won't be able to use heloc.

$$B' = \tilde{B}' + \max\{0,\ (1 - t - t_F)P_i - (r_m + 1)D_i\} \tag{15}$$

She pays the foreclosure cost t_F as well as the utility cost of foreclosure and of moving. There is no recourse in the model: if the proceeds from selling a house are less than the outstanding mortgage, the household is not responsible for the rest of the debt.

To understand the pros and cons of default, consider a household who can no longer afford mortgage payments. She still has two options: to default or to sell the house. Default has extra monetary and utility cost and does not allow her to buy a new house right away. If the household is *above water*, i.e. $(1 - t)P_i > (r_m + 1)D_i$, it is strictly better to sell the house. If she is under water, the decision is driven by the utility cost of foreclosure and the option value to buy a new house (though the option value is small because she is not likely to have enough cash for a downpayment after repaying a part of the mortgage out of pocket).

2.2.4 Demand and equilibrium

Solution to individual household's problem gives policy functions for all decisions including housing. The demand for housing is discrete (0 or 1 for each type) and I write it as functions of P_1 and P_2 given all the other state variables fixed.

I find the aggregate housing demand by integrating the individual demand with respect to all the variables except P_1 and P_2.

Each household has 11 state variables, 2 of which are prices, 1 is the state of the business cycle (Boom or Bust), and 6 more are the individual characteristics observed in the SCF data: age, employment, income[12], housing, non-housing networth, and mortgage.

The unobserved variables are 2 more individual characteristics: the realization of the moving shock M and the knowledge about the subsidy S. While the exact realization of moving shocks is not observed, the ex ante distribution is given. The knowledge about subsidy is the same across all the households: the share ω knows that the subsidy is available, and the share $1 - \omega$ does not, so I integrate over it as well by taking weighted average with weight ω.

[12] See Section 3 for the details about the transition from income to the step on the job ladder.

The integration gives the functions $H_1(P_1, P_2)$ and $H_1(P_1, P_2)$. To find equilibrium, it is enough to solve the system $H_1(P_1, P_2) = \bar{H}_1,\ H_2(P_1, P_2) = \bar{H}_2$ in each state (Boom and Bust). Note that the house prices in each state can be determined separately because the expected distribution of future prices is a function of the current prices only (with growth rates depending on the state, but given as parameters).

2.3 Computation

The one computationally cumbersome step is solving the individual problem. It involves 11-dimensional state space and 7-dimensional decision space. Local solution methods are not applicable in this problem for two reasons. First, the distribution of individual characteristics is very disperse, so that there is no single point in the state space that is good enough to approximate around. Second, the choice set is large and allow households to move far within the state space, making any local approximation too inaccurate.

Given the highly nonlinear structure of the problem that includes occasionally binding constraints and default decisions, I choose the most robust and reliable solution method – value function iteration on a grid. The finite horizon ensures that the exact solution can be found in L steps, and contraction mapping is not required[13]. I do linear interpolation in between grid points to ensure it is robust and fast.

Optimizing the implementation of the algorithm and using more computing power allows me afford a fine enough grid of approximately 250 million points for the state space, that is approximately 90 billion points if the choice set is included.[14]

2.4 Discussion

2.4.1 Model structure, preferences, and housing

Lifecycle structure (finite horizon) allows to capture the heterogeneity of agents by age, that is important for the dynamics of income and for the long-term decisions like housing choice and mortgages. Additionally it allows the moving shocks to be consistent with the large variability of moving rates by age (e.g. it is about 3 times higher for ages 25-30 as compared to ages 45-50, for more details, see Benetsky et al. (2015)).

Cobb-Douglas preferences over housing and consumption are consistent with the relatively stable income shares spent on consumption and housing in the data.

[13] I have also experimented with infinite horizon version of the model, and it converges as well.

[14] To access more computing power, I use GPU computing and Amazon Cloud p2.8xlarge workstation with total 35 teraflops of computing power (single precision), that is equivalent to about 500 average laptops. Similar GPU computing options are available from Google and Microsoft.

The model has all the main features that make housing special as compared to other assets: houses are *indivisible*, *illiquid*, *collaterizable*, pay *non-tradable dividends*, and have highly *inelastic supply*. I model indivisibility with a small finite number of housing types (rental apartments and two types of houses) and illiquidity with an extra transaction cost. Houses are used as collateral for mortgages and HELOCs. Dividends on houses come in terms of utility that is non-tradable. The supply of houses is fixed in the model.

2.4.2 Financial markets

The model is a small open economy with respect to financial markets: all interest rates are given. They are not constant though, but they follow the boom-bust cycle to match the observed changes in the data. While open economy assumption does not allow to study the responses of interest rates to the endogenous variables in the model, it is a useful (and a common[15]) assumption in the housing literature for 3 reasons. First, it simplifies the computation and allows to have more structure in the individual problem (more financial instruments, defaults, etc). Second, it is robust to misspecification of why interest rate move. Third, a good model with endogenous interest rates should match the observed rates so that their path would be the same as in a model which takes the rates from the data.

The model is designed to study the bottom 90% of the US population by income. This approach is applicable to the housing market, because the market is segmented so that the rich people price only the very top tier houses. Further, the unemployment risk, that is the main focus of this paper, matters mostly for the bottom 90% of the population, because the rich do not face high risk of losing a job or are self-insured. Focus at the bottom 90% allows me to abstract from the stock market: in the SCF data, the average ratio of the stock holdings to assets among the bottom 90% is 1.2% in 2007 and 1.1% in 2009.

The financial market in the model captures the main financial products used by US households. In the data, the bottom 90% save almost entirely into deposits, but use multiple ways to borrow: most people have credit cards, most homeowners have mortgages, and 14% homeowners used HELOC in 2007 [16]. The model has all three ways to borrow, and a single financial asset (deposits). The banks do not disclose the exact formulas for the credit card limits, but the two main factors are credit score and income. In the model, the credit limit is proportional to income, that may be a reasonable approximation. The credit limits on mortgages and HELOC in the model are formulated following the data very closely. Mortgages in the model and most mortgages in the data require a downpayment

[15]See e.g. Kiyotaki, Michaelides, and Nikolov (2011), Landvoigt, Piazzesi, and Schneider (2015), Sommer, Sullivan, and Verbrugge (2013).

[16]The population mean of HELOC balance was similar to the credit card balance: $4600 and $5300 per homeowner, while for those who have positive HELOC balance, the mean balance is $32200.

(proportional to the value of the house), and have limits formulated in terms of the ratio of annual payment to income. Similarly, HELOCs usually allow to borrow up to the point in which the sum of the mortgage and HELOC balances does not exceed a certain percentage of home value - this is exactly how the limit is formulated in the model.

The model has a simplified version of the Home Affordable Modification Program (HAMP), that is the main policy implemented during the Great Recession to help highly leveraged homeowners afford their mortgage payments. The main requirements for the eligibility are (in data): to have payment to income ratio over 31%, to have trouble making the mortgage payments, and to be able to make payments after they are reduced. The average amount of subsidy is 40% of the mortgage payment. The model approximates the eligibility requirements by lower and upper limits on payment to income ratio and by excluding the high income group.

2.4.3 Income process

I start with the standard approach and augment it with labor search and unemployment scar to make it consistent with the empirical literature on the consequences of unemployment.

The standard income process in macro literature is composed of AR(1) persistent component and an iid transitory shock. For computational tractability the persistent component is usually approximated by a 3-state Markov chain using Rouwenhorst (1995) method. Good examples of recent housing papers following the above approach are Mitman (2016) and Garriga and Hedlund (2016). Kopecky and Suen (2010) test five approximation methods and find the Rouwenhorst method better than most alternatives for both approximating AR(1) and for the quality of model simulated results (for RBC and Aiyagari (1994) type models).

Davis and von Wachter (2011) find that separation from a job leads a large and persistent loss in future income, that is about twice bigger in recessions. They also show that workers' anxiety about their labor market prospects closely matches the data. These findings suggest that a good model of labor market may help match people's expectations and decisions based on those expectations.

My modeling of income process is similar to Jarosch (2015) who matches the consequences of job loss in German data and finds them consistent with Davis and von Wachter (2011) empirical estimates for the US data.

2.4.4 Expectations

Housing papers use three types of expectations: rational expectations, various types of limited rationality, and expectations measured from surveys.

While rational expectations are common in other areas of macroeconomics, they are rare in housing papers for two reasons. First, housing expectation surveys show evidence that rational expectations assumption might be violated to a large margin. Case, Shiller, and Thompson (2012) find house price expectations during 2003-20012 be over-optimistic and not sensitive enough to observables, as compared to an econometrician's expectations. Second, many housing models (including the one in this paper) have heterogeneous agents, that makes the whole distribution of individual characteristics a state variable and solving for a rational expectations equilibrium infeasible.

Most housing papers utilize an assumption of limited rationality. A good examples are Garriga and Hedlund (2016) that uses approximate aggregation and Branch, Petrosky-Nadeau, and Rocheteau (2016) that suggests a version of adaptive learning. Though limited rationality is frequently a useful approach, it requires specific assumptions on how expectations are formed and so is vulnerable to misspecification. Further, limited rational expectations are vulnerable to misspecification in other blocks of the model, as expectations respond to endogenous variables in a particular way, not consistent with mathematical expectation. Finally, modeling limited rationality in a way consistent with the observed survey data on expectations is a challenging task, not yet solved in the housing literature.

In this paper, I use directly measured survey expectations. This approach also has certain limitations that I am fully aware of: it does not allow expectations to respond to endogenous variables in the model, so that there is no amplification of shocks through their effects on expectations. In particular, this limits the interpretation of policy experiments as they do not affect expectations. Though, given the empirical findings that survey expectations are not very sensitive to observables, and in particular given the observed small shift in survey expectations in response to the financial crisis, these concerns are likely to have only limited importance in my paper.

At the same time, the approach has important advantages. First, it is not subject to the problems of rational expectations or limited rationality models mentioned above. Second, while I do not take a stand on modeling limited rationality, the expectations in my exercise are consistent with the survey data by construction so that a good model of limited rationality would produce the same expected house prices. Third, using survey data from different years allows me to study the effect of the observed shift in expectations on the households' choices and on the equilibrium. Finally, this approach makes solving for the equilibrium computationally simple that allows me to have more details in the rest of the model. An examples are rich heterogeneity and a rich set of borrowing instruments with conditions changing over the business cycle. Having these details is quantitatively important, because the changes in conditions are large, vary across instruments, and different subsets of households are sensitive to distinct conditions.

3 Quantitative implementation

I use the Survey of Consumer Finances 2007-2009 panel data for the initial distribution of age, income, assets, liabilities, employment, and homeownership. I keep only the households for which the head of the household is 21-60 years old, is in labor force and has annual income below $180,000 (90th quantile of the income distribution). For the employed, I additionally require the share of labor income in total income to be no less than 50%.[17] My sample consists of 6062 households.[18]

3.1 Exercise

My modeling of expectations allows to solve the model separately in Boom and in Bust, i.e. the equilibrium prices in Boom are not needed to find the equilibrium prices in Bust, and vise versa. This simplifies the computation and allows me to use the observed distribution of households from SCF data in both cases as opposed to starting from one distribution and looking for a long run steady state that is likely to differ from the data.

I do two separate exercises:

Exercise 2007: start from SCF 2007 distribution and Boom state

Exercise 2009: start from SCF 2009 distribution and Bust state

In both exercises I find the equilibrium prices and choices for the current state only (Boom in 2007 and Bust in 2009)

Boom and Bust are the states of the model, while *Exercise 2007* and *Exercise 2009* are the actual exercises I do with the model. Though the exercises are separate, there is only one set of parameters for Boom that is used in both exercises, and one set of parameters for Bust that is also used for both exercises. Households fully understand the Markov process for Boom-Bust transition so that the parameter values for both Boom and Bust may matter for the equilibrium in both exercises.

[17] I also drop households who (1) live on a farm or ranch, (2) have financial assets (excluding retirement savings) greater than $570,000 (that is 10 * mean labor income), (3) have financial assets (including a half of retirement savings) greater than $1,000,000, (4) have housing wealth greater than $570,000, or (5) have mortgage debt greater than $570,000. All financial data are in 2007 USD (I use CPI inflation between 2007 and 2009, that is 4% total).

[18] This includes replicates, see the description at the bottom of the 2007-09 Panel Survey of Consumer Finances webpage for more detail.

The parameter choice is $P_{Boom \to Bust} = 0$ and $P_{Bust \to Boom} = 0.25$ (explained and motivated below), therefore the equilibrium in *Exercise 2007* depends on the Boom set of parameters only, while the equilibrium in *Exercise 2009* depends on both sets of parameters.

The reason I have to treat these as separate exercises is the fact that the distribution of agents is different. When I switch from *Exercise 2007* to *Exercise 2009* to study the housing bust, the distribution is not the one that arises from choices made by households in *Exercise 2007*. Though I show in the *Model fit* section that their choices generate a very similar distribution[19], so it is likely that the results are similar if the choices are used in the second exercise instead of the data. Still, using the data allows me to evaluate the effect of the observed change in the distribution, that includes the stock market crash, deleveraging and everything else that happened to households' balance sheets between 2007 and 2009.

3.2 Parameter choice

I split the parameters into *external* and *internal*. *External* parameters are measured directly from data (e.g. interest rates) or chosen based on the literature (e.g. risk aversion). The values for the internal parameters are chosen so that moments of endogenous variables in the model match their data counterparts. The full list of *internal* parameters is: the service flow from houses, the discount factor, and the utility costs of moving and of defaults.

All the internal parameters are chosen based on the *Exercise 2007* only. Only external parameters change their values over the business cycle and $P_{Boom \to Bust} = 0$. This way I ensure that the choice of internal parameters is independent of the data on the housing bust. Therefore, all the differences between *Exercise 2007* and *Exercise 2009* are not targeted.

Below I explain the choice of all the parameters, sorted by topic.

3.3 Housing

I set the Cobb-Douglas weight on housing to 0.2, that is a standard value in the literature and reflects long term average spending share on housing in the US. The parameters for the housing services H_1 and H_2 target the house prices in 2007. I use median house prices from Zillow in May 2007 for the bottom tier (\$114,000), the top tier (\$348,000), as well as the median house price (\$191,000). I target the price of a small house $P_1 = (114,000 + 191,000)/2 = 153,000$, and the price of a large house $P_2 = (191,000+348,000)/2 = 270,000$. This requires $H_1 = 7.9$ and $H_2 = 94$ so that switching from renting to owning a small house is equivelant to 68% increase in consumption ($H_1^{\frac{\alpha}{1-\alpha}} = 1.68$), and switching from small to large house – to a 86% increase in consumption.

[19] To account for the stock market crash, I use the realized returns on savings in this comparison.

Rental rate is \$10,000 per year, that is roughly the US average in 2007. **Property taxes** vary across states, but the median rate is close to 1%. A standard value for the **maintenance cost** in the literature is also 1%. I set the sum of those costs to 2% of the house value.

Housing transaction costs capture not only the taxes and real estate fees paid by the seller but also the costs associated with how long it takes to sell a house. The values of transaction costs in the literature vary between 6% and 10%, and usually a larger value is used in the housing bust, because the time on market more than doubled between 2007 and 2009 (Garriga and Hedlund (2016)). I set the transaction costs to 6% in Boom and 9% in Bust.

Housing supply is estimated from homeownership in SCF. For each year (2007, 2009), I define houses with the reported value above median as large, and the rest as small. So I assume that always a half of houses are small, but the total number of houses may differ between 2007 and 2009. The resulting supply (expressed relative to the population, i.e. as homeownership rate) is $\bar{H}_1 = .319$, $\bar{H}_2 = .318$ in Boom (2007) and $\bar{H}_1 = .338$, $\bar{H}_2 = .321$ in Bust (2009). $\bar{H}_1$ does not exactly equal $\bar{H}_2$ because the sample is discrete and the sample weights are disperse.

3.4 Moving shocks

Moving shocks capture the motives for moving that do not arise endogenously within the model. To estimate the moving probabilities, I use the survey on reasons to move that was a part of SCF 2007-09 panel. The reasons I consider exogenous are family (e.g. getting married), health, taste changes[20] and changing jobs without becoming unemployed[21]. 24% households in my sample moved between 2007 and 2009, that corresponds to an annualized moving rate of 13%, more than half (8% annualized) being for exogenous reasons. I compute moving shares separately for homeowners and renters (60% and 64% correspondingly). Then I use the US Census data for moving rates by age and apply those shares to predict exogenous moving rates by age and homeownership for my sample[22].

Moving cost is set to 16% utility so that the total moving rate in the model is 13%. This implies 5% households moving for endogenous reasons.

[20] The exact survey answers I use are *shorten commute, wanted better/different location, health reasons, new spouse/partner, divorced/separated from spouse/partner, needed more/different space, to be near relatives.*

[21] On the job search is not a part of the model so it creates an exogenous reason to move.

[22] I do not use SCF to estimate moving rates by age and homeownership, because it has too few observations for some the 40 age groups I have given not many homeowners move. For more details on the US Census data on moving, see Benetsky et al. (2015).

TABLE 1: Parameter values.

Parameter	Value	Internal	Source / Target
Housing			
Spending share on housing, α	0.2	N	Standard
Housing services, (H_1, H_2)	(7.9, 94)	Y	House prices in 2007 (Zillow)
Rental cost, p	\$10,000 / year	N	US average 2007 (Corelogic)
Maintenance cost + property tax	2%	N	Standard
Housing transaction cost	6% → 9%	N	Standard
Utility cost of moving	16%	Y	Total moving rate 2007 (SCF)
Housing stock $\bar{H}_1, \bar{H}_2$	.32, .32 → .33, .32	N	SCF
Finance			
Deposit: interest rate	-2.7% → -1.7%	N	FED
Mortgage: downpayment, d	12% → 18%	N	Standard, see text
Mortgage: payment/income ratio	50% → 40%	N	Standard, see text
Mortgage: amortization rate, δ	1/30 → 1/25	N	Mortgage term = $1/\delta$
Mortgage: utility cost of default	0.5%	Y	Mortgage delinquency rate 2007
Mortgage: origination cost	\$1700	N	Standard
Mortgage: foreclosure cost	10%	N	Standard
Mortgage: interest rate	3.6%	N	FED
HELOC: loan to value	85% → 60%	N	Standard, see text
HELOC: fixed cost	\$100	N	Standard
HELOC: interest rate	5.3% → 1.6%	N	FED
Credit card: debt to income	100% → 80%	N	see text
Credit card: util. cost of default	37%	Y	Credit card delinquency rate 2007
Credit card: interest rate	10.4% → 11.6%	N	FED
Mortgage policy			
Subsidy as share of payment	0% → 40%	N	HAMP
Lowest payment to income ratio	31%	N	HAMP
Highest payment to income ratio	52%	N	pay/inc after subsidy < 31%
Income groups eligible	W_L, W_M	N	*show evidence of financial hardship*
Share of households aware	44%	N	HAMP application rate 2009
*Income process**			
Unemployment replacement rate, z	0.7 → 0.5	N	match Davis and von Wachter 2011
Human capital transition, P_{up}, P_{down}	0.05, 0.5	N	match DW2011
Finding rate, f_H	0.9 → 0.6	N	match DW2011, mean: Shimer 2012
Finding rate for long term unempl., f_L	0.6 → 0.3	N	match DW2011
Separation rates, $s_1,\ s_2,\ s_3$	0.3, 0.2, 0.1	N	match DW2011, mean: Shimer 2012
Prob. of long term unempl., P_{LTU}	0.1 → 0.3	N	Kosanovich and Sherman 2015
SD of transitory shock	20%	N	Storesletten et al. (2004)
Payroll tax rate	20%	N	Standard
PAYG pension share	50%	N	see text
Other parameters			
Discount factor, β	0.91	Y	target mean savings in 2007
Risk aversion, γ	2	N	Standard
Transition prob: Boom to Bust	0	N	see text
Transition prob: Bust to Boom	0.25	N	see text
Expected house price growth g_{stay}	6.6% → 0%	N	Case, Shiller, Thompson (2012)
Expected house price growth g_{switch}	-20% → 20%	N	Case, Shiller, Thompson (2012)

Note: The values that change over the business cycle are reported in the form *(Value in Boom → Value in Bust)*. For example, the transaction cost of selling a house (line 5 in the table) is 6% in Boom and 9% in Bust. A parameter is considered internal if at least one moment of an endogenous variable in the model is used to choose the value of this parameter. Other parameters are based on the literature or estimated directly from the data. *I consider the income process exogenous (as opposed to modeling demand and supply in the labor market). Therefore, I treat all the parameters of the income process as external, even though some of them are chosen so that the moments of the income process match the data or empirical evidence.

3.5 Finance

Mortgage downpayment in the model tightened from 12% in Boom to 18% in Bust. The approach to parameterizing downpayment constraint varies a lot across papers. Kaplan, Mittman, Violante (2017) use -10% for Boom and 5% for Bust, Greenwald (2016) has average downpayment 15%, in Kiyotaki, Michaelides, and Nikolov (2011) it changes from 10% to 100%. The most standard downpayment in the US is 20% but many banks offered better conditions during the housing boom. According to Freddie Mae data (Greenwald (2016)), about 10% new mortgage originations in 2006Q1 had zero downpayment, 15-17% had 10% and 5% downpayment respectively, and about 35% had 20% downpayment. After that the constraints tightened considerably, e.g. in 2014Q1 almost no banks offered mortgages without downpayment. Therefore, my parameterization is close to the data, though being relatively conservative as compared to other papers.

The **payment to income ratio** required by banks goes up from 40% in Boom to 50% in Bust. These numbers follow about 90th percentile of PTI distribution in Greenwald (2016) for 2006Q1 and 2014Q1 respectively. The literature uses all kinds of constraints from above 100% in Boom to 0% in Bust, so I am again on a more conservative side.

Mortgages in model have infinite term but are geometrically declining so that the inverse **amortization rate** is an approximation for the mortgage term. The most common term in US is 30 years, but there is a significant share of 15-year mortgages as well. In Boom banks were offering mortgage contracts with back-loaded payments making them similar to even longer term mortgages. Most papers use $\delta = 1/30$. I set $\delta = 1/30$ for Boom but 1/25 for Bust to account for the fact that there was almost no back-loaded mortgages and still a positive share of 15-year mortgages.

The **foreclosure cost** is 10% that is standard for the literature. The extra **utility cost of foreclosure** is small (0.5% utility) and targets the delinquency rate in 2007 (3%). It is low because the default on a mortgage initiates a foreclosure (10% monetary cost) and forces the household to move (16% utility cost + 6% transaction cost of selling a house).

The origination cost is \$1700 that is also somewhat standard in the literature.

Home Equity Lines of Credit (HELOCs) have a fixed cost of \$100 (average for US banks). The total borrowing via Heloc and Mortgage as a ratio to the house value cannot exceed 85% in Boom and 60% in Bust. The actual credit limits vary across banks. During the housing boom, many banks had limit between 80% and 85%. I use the limit of 85% for the Boom. The average HELOC balance per homeowner in *Exercise 2007* is close to the one in the data (\$3500 model vs \$3800 data), that proves this strategy to be reasonable. During the bust, most banks tightened the limits, and I use the limit of 60% for the Bust.

Credit card debt in the model represents all sorts of unsecured borrowing. There is not much data available to estimate credit limits. An average household has 4-6 credit cards[23] with a limit about $3000-5000 each, that gives $12000-$30000 range. The mean credit card limit in my sample is $17500 in 2007 and $17000 in 2009 and falls in this range. Mian and Sufi (2013) report a larger $1500 decline in credit card limit in their sample over 2006-09. The average ratio of credit card limit to income in SCF is 33% in both years but many have higher limits, for example 90th quantile is 80%. These are the limits on credit cards only, while most households have an option to open new credit cards and to apply for other forms of unsecured credit that we do not observe. Therefore, I set higher limits for the total unsecured credit in the model: the maximum ratio of credit to income is 100% in Boom and 80% in Bust. The utility cost of credit card default is 37% to match the delinquency rate of 4% in 2007. This is high compared to the utility cost of mortgage default, but if the foreclosure and moving associated with mortgage default are taken into account, the costs are more similar.

Interest rates. I use Federal Reserve data for interest rates on mortgages and credit cards. For HELOC, I use the prime rate + 1%, as it is the most standard HELOC rate. For deposits, I use zero nominal interest rate. I convert the nominal rates to real rates using 2.7% inflation in Boom and 1.7% inflation in Bust.[24] The resulting real rates are in Boom -2.7% deposit, 3.6% mortgage, 5.3% HELOC, 10.4% credit card, in Bust -1.7% deposit, 3.6% mortgage, 1.6% HELOC, 11.6% credit card.

3.6 Mortgage policy

The policy is similar to the Home Affordable Modification Program (HAMP) implemented in US starting 2009. In the data, HAMP subsidizes poor leveraged homeowners, and the median ratio of the subsidy to the mortgage payment varies by states between 30% and 50%, with the median for the US around 36-37%. In the model it is a subsidy equal to 40% of annual payment.

HAMP eligibility requirements include 13 criteria, the most important ones can be summarized as

a) payment to income ratio above 31%

b) show evidence of financial hardship or high risk of default in foreseeable future

c) be able to afford the reduced mortgage payment

[23] That is 2-3 per person multiplied by 2 adults in an average household.

[24] Actual CPI inflation was 2.7% in 2007, 3.8% in 2008, and -0.4% in 2009. For 2007 I use the actual inflation, but I do not find using negative inflation for 2009 reasonable as it would imply expected deflation and counterfactually high interest rates for the whole time the economy stays in Bust, that is on average 4 years in the model. Therefore I use the average inflation between 2008 and 2009.

In the model, I use the following eligibility criteria

a) payment to income ratio above 31%

b) be in W_L or W_M group by human capital (this is roughly below 60% quantile by income, because my sample includes the bottom 90% by income)

c) payment to income ratio below 52% (this way I guarantee that the payment to income ratio after subsidy is below 31%). For the unemployed I use the income that they would have had if they were employed – to account for the fact that most people find jobs fairly quickly and that more than half of the applicants reported loss of income as the main reason they applied for HAMP.

In the model, 7% of homeowners with mortgages meet the above criteria. In absolute terms it is about 2.73 million households. This is close to the goal set by HAMP – to have 3-4 million households. In the data, though, only 1.2 million applied by the end of 2009 – this is one of the reasons why HAMP was criticized for the lack of information provision so that many households who were eligible did not apply. Assuming all who applied are in my sample, only 3% of my sample applied. To make the model match the application rate in the data (and to account for the lack of information), I choose the share of households aware about the subsidy $\omega = 3\%/7\% = 44\%$.

3.7 Income process

Households work for 40 years and are retired for the next 20 years. I estimate the lifecycle profile of income using the 2007 total gross salary and wage income (I refer to it as labor income) of the employed only from the Survey of Consumer Finances 2007-09. I split the employed into three groups of equal size using the SCF sample weights. Then for each of these groups, I compute the average income within each single age group. Finally, I fit a quadratic polynomial to each of the three profiles. The resulting profiles are in Appendix.

The job separation, finding rates, the unemployment replacement rate, and the transition probabilities for human capital are chosen so that the mean separation and fining rates in the simulated time series are consistent with annualized rates from Shimer (2012) and the income losses from unemployment are consistent with Davis and von Wachter (2011). More specifically, the separation rates are $s = (0.1, 0.2, 0.3)$, the job finding rates (f_H, f_L) are (0.9, 0.6) in Boom and (0.6, 0.3) in Bust, and the unemployment replacement rate z is 0.7 in Boom and 0.5 in Bust.

Table 2 compares the consequences of job loss in the model and in the data. Davis and von Wachter (2011) focus on workers with at least 3 years of tenure and report short term income

TABLE 2: Loss of labor income after a separation, in percentage to the mean income 2-5 years prior to the separation.

	Short-term (2 years)		Long-term (10 years)	
	Boom	Bust	Boom	Bust
3+ years tenure, Data	20	30	10	20
3+ years tenure, Model	18	27	12	17
Average job loser, Model	14	24	9	14
1-2 years tenure, Model	9	20	5	9

Note: The loss is measured relative to the control group that consists of workers who have not separated from a job and have the same distribution of human capital as the lob losers a year prior to their separation. Data is the evidence from Davis and von Wachter (2011). Average stands for a representative job loser.

loss (in 2 years after separation) of about 30% in recessions and 20% in expansions; long term loss (in 10 years after separation) of about 20% in recessions and 10% in expansions. The corresponding losses for the workers with at least 3 years tenure in my model are 27% and 18% in 2 years; 17% and 12% in 10 years[25]. Most losses and the differences between Boom and Bust in the model are smaller than the ones reported by Davis and von Wachter (2011). This way I follow a more conservative approach to make sure the model does not imply too large losses that differ too much over the business cycle.

To the best of my knowledge, there is no empirical evidence for the losses without imposing tenure restrictions, but most discussions in the related literature suppose they are smaller. This is true in the model: the losses of workers with 1 or 2 years of tenure (that is the complement of the sample reported above) are 20% and 9% in 2 years, and 9% and 5% in 10 years (for the Bust and Boom correspondingly).

The payroll tax rate is 20% that is close the US average.

The retirement replacement rate is 45% (US average), and the share of PAYG retirement benefits is 1/2. This means that when households retire, they receive PAYG benefit equal to 1/2 * 45% * last year human capital[26]. This also implies that the other half of the benefits comes from the retirement savings accumulated in their accounts. I observe these accounts in SCF and include 1/2 of the balances into non-housing networth[27]. This makes

[25]To evaluate these average losses, I run 10,000 independent simulations of 40-year long lifecycle, half of which start in Boom and half start in Bust. This is not a part of *Exercise 2007* or *Exercise 2009*, in which I do not run dynamic simulations and only solve for equilibrium in the current year.

[26]I use human capital not income, i.e. I drop the effect of unemployment during the last year of working age and the transitory shock. This is an approximation to the fact that PAYG benefits are not determined by short term shocks.

[27]I also experiment with 1/4 - 3/4 PAYG share which means 3/4 - 1/4 retirement savings are included in

the retirement benefits be less sensitive to the last year's earnings (otherwise the risks are too high and the households make counterfactually high precautionary savings). This is also a rough approximation of the fact that retirement savings are partially accessible before retirement. Most plans allow to extract savings at a penalty for any reason and without a penalty for a particular set of reasons (which usually includes downpayment for housing, unexpected medical expenses, etc.)

3.8 Other parameters

I choose the discount factor $\beta = 0.91$ to match the average savings. The risk aversion is standard $\gamma = 2$.

The probability of transition from Boom to Bust is 0 for the following reasons: (1) the housing bust was largely unexpected, (2) to make sure that the internal parameters do not use any data on housing bust, (3) simplicity. I also experimented with probabilities up to 10% without large changes in results. The probability of transition from Bust to Boom is 25%, and I experiment with probabilities between 10% and 30%, again without large changes in results[28].

The house price growth expectations equal the average 10-year expected growth rate of house prices from Case, Shiller, and Thompson (2012) for 2007 (Boom) and 2009 (Bust) assuming the average inflation rate of 2.5%: 6.6% for Boom and 5% for Bust. If the current state is Boom, households expect house prices to grow for $g_{stay}^{Boom} = 6.6\%$ annually forever. If the current state is Bust, they expect house prices to stay constant while the economy stays in Bust ($g_{stay}^{Bust} = 0$), and to go up by $g_{switch}^{Bust} = 20\%$ in the period when it switches to Boom. This implies the expected growth rate in Bust 0.25 * 20% = 5%. Households in Bust realize that after the economy switches to Boom (and the house price grows by 20% once), the growth in all the periods after that will be 6.6% forever. The parameter g_{switch}^{Boom} does not play a role in the baseline model, because $P_{Boom \to Bust} = 0$. For the robustness exercises when I allow $P_{Boom \to Bust} > 0$, I use $g_{switch}^{Boom} = -20\%$ for symmetry.

4 Results

First, I check the cross-section fit of *Exercise 2007*. Then I compare *Exercise 2009* to *Exercise 2007*, decompose the housing bust into the effects of separate shocks, and study the

non-housing networth. There are no large changes in results.

[28]The results of the experiments are predictable. Both positive probability of transition from Boom to Bust and larger probability of transition from Bust to Boom make the equilibria in these two states closer to each other. Lower probability of transition from Bust to Boom makes the equilibria differ more.

role played by the moving shocks.

4.1 Model fit

Figure 2 shows the model performance in *Exercise 2007* in the cross-section of savings, mortgage balances, homeownership, moving, and total networth by age. All the internal parameters are chosen to help the model match the aggregate data on house prices, savings, moving, and delinquencies in 2007. The initial distribution of households in the model is taken from the 2007 data, but the model does well in matching the *choices* made by the households afterwards, that were not targeted.

The top left panel shows the distribution of non-housing networth (I refer to it as *savings*) by age groups. Black bars represent the initial distribution: by construction, it is the same in the model and in the data. The choices made in 2007 for the next year do not have to match the observed savings in 2009 for two reasons: (1) 2009 is in two years after 2007, (2) there was an unexpected financial crisis that affected returns and unobserved intermediate choices in 2008. To make these more comparable, I apply the realized 2008 returns to the savings, accounting for the share of savings held in stocks [29]. The resulting savings distribution (blue bars) is similar to the data and shows the same pattern: the young do not save much because they expect the income to rise, then the middle aged start saving for retirement and save more the closer to retirement they are[30]. The financial crisis hit the savings of all the age groups.

The mortgage balances are small for the young because they do not have high enough income to satisfy the payment-to-income constraint, and not enough savings to make a downpayment. Most people take mortgages only in their late twenties or early thirties – this is reflected by the highest mortgage debt in these age groups. The model follows this pattern similarly to the data[31].

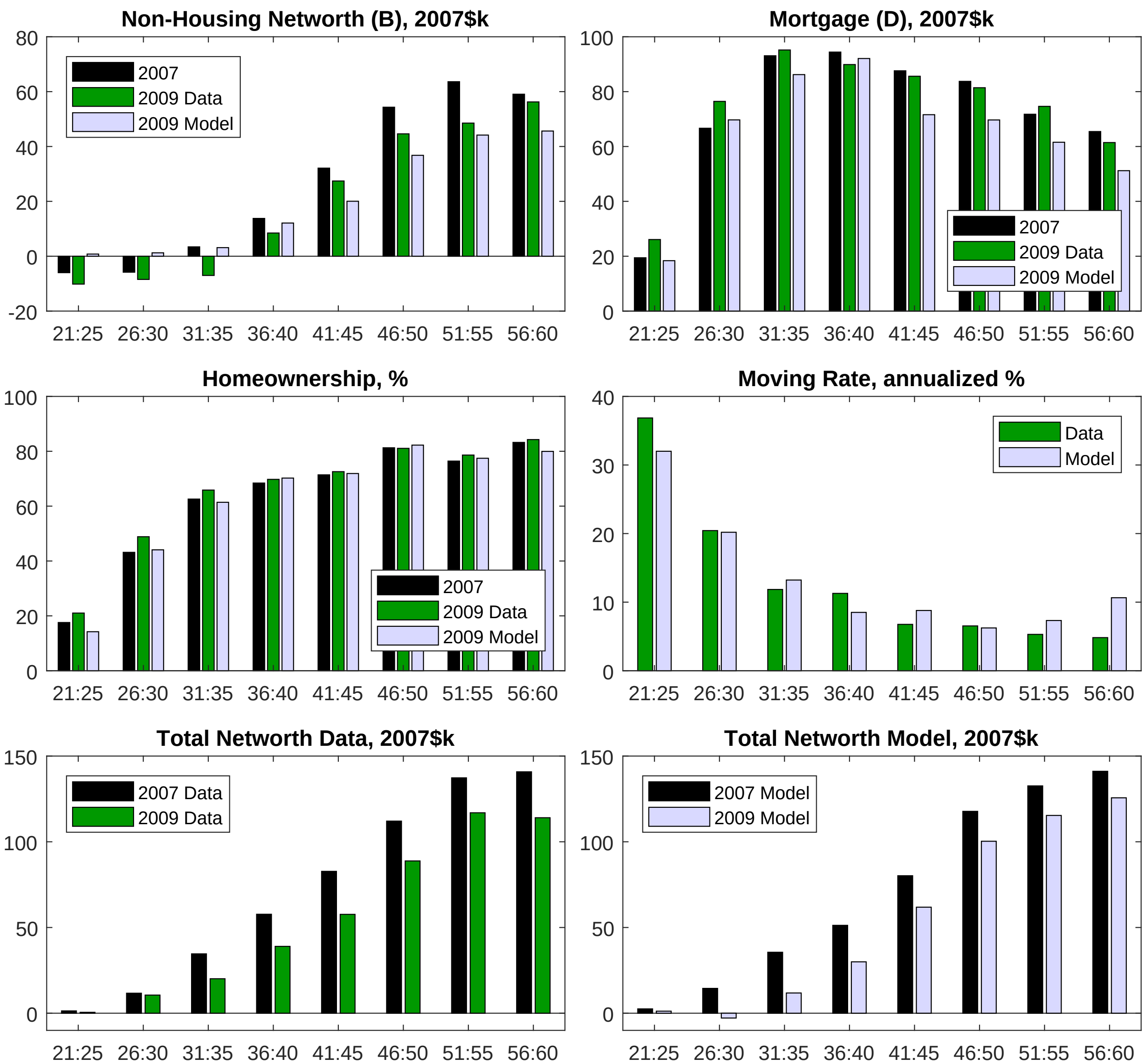
The homeownership rates for 2009 Model are calculated from choices in *Exercise 2007*. Both in the model and in the data, the first two years of the housing bust did not result in any significant change in the distribution of homeownership by age. Though there is a

[29] The share of savings held in stocks for the households with positive savings is 14% in my sample (it includes direct as well as indirect stock holdings in mutual funds and retirement accounts). I apply the realized returns on SP500 (-37% real returns) to the stock holdings, Bust r_d to the rest of positive savings, Bust r_c to the negative savings of renters, and the average between the Bust r_c and the Bust r_h to the negative savings of homeowners (credit card balances were roughly equal to heloc balances). It is still a rough estimate, but it is used only for this single comparison and does not affect anything else.

[30] There is a bit less dispersion across age groups in the model than in the data: the young cohorts borrow less, and the old save less. Many households still borrow in cross section, and the young borrow more than the old. It just happens that the averages in model are all positive.

[31] To make the model choices for the next year more comparable to the data in 2 years, I apply the amortization rate δ one more time – this is why the balances in the model are lower than in the data.

FIGURE 2: Cross-section fit for the baseline model.



Note: Results of *Exercise 2007* in cross-section by age groups compared to data. The parameters target house prices, delinquencies, and the population averages non-housing networth, homeownership and moving rates. The initial cross-section distribution (labeled 2007) in model is the same as in data, but the cross-section of choices (labeled Model 2009) is not targeted and are compared to the distribution in data (labled 2009 Data). Moving rate is between 2007 and 2009, annualized using the formula $Moving_{1year} = 1 - \sqrt{1 - Moving_{2years}}$. Total networth for Model 2007 is calculated using the equilibrium *Exercise 2007*, while Data 2007 uses the observed prices. Total networth for Model 2009 is calculated using the equilibrium *Exercise 2009*, while Data 2009 uses the observed prices.

lot of moving within the age groups, especially the young. The homeownership rates are increasing in age and reflect the behavior discussed above: the young mostly do not own, and many people buy houses when they are 26-35 years old. The population of buyers is relatively young and vulnerable to credit tightening – this is one of the reasons why credit conditions have large effect. Another reason is moving.

The model captures moving rates by age: the young move more than the old so that the population of movers has relatively low income and savings, and therefore is more credit constrained. Many moving renters are just about to buy a house (are in age groups with highest probability to switch from renting to ownership).

At the same time, the older cohorts who are mostly homeowners, are not completely out of the housing market like it would happen in a model without moving shocks. Therefore the young care even more about credit and labor conditions as they realize the risk of moving later.

The bottom panels shows the total networth that equals savings minus mortgage plus the value of the house. Savings and mortgages in 2007 are the same in model and data, but the value of houses differ. In the data, for each household I use the value reported by this household. In the model, there are two types of houses, and I use the equilibrium prices. A house is small (and the value is P_1) if its value is below the median reported, and it is large (P_2) otherwise. In 2009, the savings and the mortgages are the same as in the top panel. The distribution of houses is calculated from the choices made in *Exercise 2007* and the equilibrium house prices in *Exercise 2009*.

4.2 Housing bust

Table 3 compares the equilibrium in the model in *Exercise 2007* and *Exercise 2007* to the data. The preference parameters help the model match the delinquency rates and the prices of both house types in Boom. It follows that it matches also the total housing networth and the mean house price (defined as average between small and large house).

No moment in the *Exercise 2009* is targeted, and no internal parameter changes between *Exercise 2007* and *Exercise 2009*. All the differences between the equilibria in *Exercise 2007* and *Exercise 2009* result from the changes in external parameters and in the distribution of household characteristics in the SCF panel between 2007 and 2009.

The housing bust in the model is similar to the data. Both in the model and in the data 2009, credit cards delinquencies almost doubled, and mortgage delinquencies almost tripled, while savings marginally increased, and house prices fell.

The drop in house prices in the model is larger than in 2009 data but is close to the trough

TABLE 3: Housing boom and bust in model and data.

	Delinquency rate, %		Networth, 2007 $k		House Price/Drop		
	Credit card	Mortgage	Non-Housing	Housing	Small	Large	Mean
Model 2007	4.1	3.0	19.4	56	151	267	209
Data 2007	4.0	2.7		58	149	264	206
Model 2009	7.2	7.5	20.2	35	32%	21%	25%
Data 2009	6.8	8.6	19.8	39	15%	15%	15%
Data 2012	2.9	10.4			33%	29%	31%
No subsidy	8.9	11.0			42%	29%	34%

Note: Compares results of *Exercise 2007* and *Exercise 2009* to the data. Networth and house prices are in thousands 2007 USD. The last row is *Exercise 2009* without mortgage subsidy.

of the housing bust in 2012. This happens because the housing market is immediately in equilibrium in the model, while in the data it takes long time for the houses to be sold and lower prices to be observed. Average time on market more than doubled and reached 50 weeks in 2009 (Garriga and Hedlund (2016)), and it is likely to be even more for the most depressed regions – this caused a lagged response in the data. The model accounts for the cost of waiting (higher transaction cost of selling a house), but it produces the trough of the bust immediately in 2009.

One of the challenging facts for the bust literature was that the prices of smaller houses fell more than the prices of larger houses. The model is able to match this fact for three reasons. First, the income process with job ladder implies that lower income households care more about the weak labor market because their jobs are less secure. Second, moving shocks reduce selection into moving so that not only rich households move and care about credit conditions and house price expectations. Third, there is no assumption that large houses can be converted into smaller ones at low cost – this captures the segmentation of the housing market and makes the demand of lower income households matter more for smaller houses.

4.3 Mortgage policy

The results above have mortgage subsidy already included. To study the effect of the mortgage policy, I remove the subsidy. The results are in the last row of table 3. In a model without subsidy, almost 9% of credit cards and 11% of mortgages are delinquent, as opposed to 7.2% credit cards and 7.5% mortgages in the baseline model. The average house price falls by 34%, that is 9% more than in the baseline model. The effect is marginally stronger for smaller houses: extra 10% drop for small houses, and 8% for large.

4.4 Decomposition

What caused the housing bust? For example, what was the role of tightened mortgage conditions: downpayment constraints, payment-to-income constraints, and fewer amortized mortgages? One way to answer the last question (and the most common way in the literature) is to study a model in which only mortgage conditions change over the Boom-Bust episode (call it *Model 1*), while all other conditions stay at their Boom levels. The difference between Boom and Bust house prices in this version of model is then the effect of tightened mortgage conditions.

But this would not be the complete answer, because in the data, mortgage conditions tightened at the same time with other conditions: if there was an interaction, the first approach would ignore it. Indeed, when the labor market is already weak, more households are likely to be affected by tightened mortgage conditions. Model 1 would then underestimate the role of mortgage conditions.

To include the interactions, I do one more experiment. I consider a model in which mortgage conditions do not change (stay at Boom levels always), but all other conditions change over Boom-Bust (call it *Model 2*). Then I compare the drop in house prices in the Model 2 to the Baseline drop. The difference between Baseline and Model 2 is the result of tighter mortgage conditions.

The results of both experiments for the mortgage conditions[32] are in the second row of Table 4. Model 1: tightened mortgage conditions produce 11.9% drop in house prices other conditions stay at Boom levels. Model 2: all other conditions combined produce only 7.5% drop in house prices. The Baseline produces 25% drop and differs from Model 2 only in one way: Baseline has tightened mortgage conditions. So I assign to Mortgage conditions 25% - 7.5% = 17.5% drop, that is indeed larger than the drop in Model 1.

Another interpretation of this approach: consider a series of experiments which start from a model with Bust=Boom, and adds differences between Boom and Bust in some order, until they are all added (as in the Baseline model). Each step contributes some drop to the house prices, and the final combined drop is 25%. If the mortgage conditions are added first, then they contribute 11.9%. If instead, they are added last, they contribute 17.5%. This interpretation means that both Model 1 and Model 2 approaches make sense and are just two extremes of a more general procedure (a shock may be added first, second, third...). One way to aggregate this is Shapley vector (Shapley (1953)), that for each shock would contain a simple average of its contribution over all possible orders. Though Shapley vector is informative in other applications, I believe the two cases I consider are more informative for

[32]The experiments are the same *Exercise 2007* and *Exercise 2009* as before, now just with fewer parameters changing between Boom and Bust.

TABLE 4: The percentage drop in the house price as a result of shocks.

	Added First	Added Last
Financial conditions	**17.8**	**20.8**
Mortgage	11.9	17.5
HELOC	3.4	2.0
Credit Card	2.1	3.0
Deposit	0.7	0
Labor conditions	**9.1**	**11.4**
Job finding rate	5.7	6.3
Unemployment benefit	3.4	6.0
Long term unemployment	0	0
House price growth expectations	2.9	6.1
Housing transaction cost	0.6	0.5
Balance sheet	-0.9	2.0
Mortgage subsidy	-10.0	-8.9
All shocks together	25	25

Note: Column 1 (labeled *Added First*) represents the fall in average house price when only one shock is in action (the one named in the row label). Column 2 (labeled *Added Last*) shows by how much less the house price falls if the shock named in the row label is removed. All numbers are in percent of the average house price in 2007.

this application as they are easier to interpret and give clear intuition about the interactions.

Each row of Table 4 presents the results of such two experiments for a subset of conditions. I compare these results to the total house price drop in Baseline model (25%), and in the drop without mortgage (34%). Financial shocks are the main driving force of the housing bust and produced between 17.8% and 20.8% drop in house prices. Within the financial conditions, the main force is tighter mortgage conditions. While these results do not sound surprising (as we are talking about the financial crisis with large role played by mortgages), most housing models are unable to produce them (or require counterfactually large changes in conditions).

Weak labor market contributes 9.1 - 11.4% to the house price drop, that is remarkably close 9.0 - 11.6% in Garriga and Hedlund (2016), who obtain the result in a very different framework: infinitely lived households (no lifecycle), standard income process, no unsecured borrowing, perfect foresight, direct modeling of housing search with time on market. So the result is robust to large changes in assumptions.

It may seem puzzling though, why the effect of labor market conditions is large in a model without unemployment scars or moving shocks. Here is the explanation. First, left tail income risk in Garriga and Hedlund (2016), is similar to the effect of unemployment scars.

There are no moving shocks in Garriga and Hedlund (2016), but it has another important mechanism that has similar effects – search in the housing market. In bust, it takes much longer to buy or sell a house. Therefore, households are less likely to trade houses when it is the most convenient for them to do so. As a result, they cannot easily avoid bad conditions, and are more concerned about them.

I further decompose the effect of labor market conditions into separate effects of lower job finding rates and lower unemployment replacement rate. Both factors influence short- and long-term loss from unemployment, but job finding rates contribute relatively more to long-term losses, while unemployment replacement rate contributes more to short-term losses. Lower job finding rates account for more than half of the effect, suggesting that long-term losses are more important.

The contribution of house price expectations is sizable 2.9% – 6.1% but not as large in Kaplan, Mitman, and Violante (2017), who conclude that expectations are single most important factor of the housing bust. Their exercise is less comparable to what I do, because the expectations are about the preferences for housing in the future, while I consider expectations about house prices. The change in expectations about preferences does lead to the change in expectations about prices in their model, but what I show is that the expectations about prices do not have very large effect on their own. So, in a way, I suggest that in their model the demand for houses falls more because households expect housing utility to fall than because they expect house prices to fall.

While the effect of illiquidity has the right sign, it is small in my model and contributes only a half percent to the housing drop. I do not interpret this as illiquidity is not important, because my modeling of it if very simple. In a richer model, illiquidity would lead to a lagged response of house prices so that they fall not immediately in 2009, but continue falling over the next years.

Balance sheet changes between 2007 and 2009 also have small effect: the contribute no more than 2%. This happens because not only assets drop in the *Exercise 2009*, but also the liabilities. Many households defaulted between 2007 and 2009, fewer households were approved new loans (especially those who were more likely to default). So the combined effect does not have to be big. Also I include bottom 90% by income so stock market crash is largely not in my sample – though given my sample covers the majority of the working age households, and the housing market is highly segmented, the balance sheet effect of the stock market crash is not likely to have large effects on median house prices (as opposed to the very large houses that are excluded from my sample as well).

TABLE 5: The housing bust in a model without moving shock.

	Delinquency rate, %		Networth, 2007 $k		House Price/Drop		
	Credit card	Mortgage	Non-Housing	Housing	Small	Large	Mean
Model Boom	3.7	0.7	19.4	56	198	369	283
Data 2007	4.0	2.7		104	149	264	206
Model Bust	3.9	3.2	5.8	96	11%	10%	10%
Data 2009	6.8	8.6	19.8	39	15%	15%	15%
Data 2012	2.9	10.4			33%	29%	31%

Note: The table compares results of *Exercise 2007* and *Exercise 2009* without moving shocks to the data. Networth and house prices are in thousands 2007 USD.

4.5 Moving shock

Table 5 shows the version of model without moving shocks. As moving shocks are the same in Boom and Bust, removing them affects both equilibria.

Boom. First, the decision to default on a mortgage depends on household's expectation of whether they move: without moving shocks virtually no households decide to default on their mortgages: the delinquency rate is 0.7% in the model vs 2.7% in the data. Though there is almost no effect on credit cards delinquencies (3.7% vs 4.1%) as they are less related to housing choices. Second, the decision to buy or sell a house (even without default) also depend on the expected moving risk, and the absense of this risk results in higher housing demand and much higher prices: average house price in *Exercise 2007* is 37% above data.

Bust. Delinquencies rise and house prices fall during the housing bust, but much less than in the Baseline model. Delinquencies on both credit cards and mortgages in *Exercise 2009* (3.9% and 3.2%) are closer to the data in 2007 (4.0% and 2.7%) than to the data in 2009 (6.8% and 8.6%). Additionally to the reasons above, there is selection into moving: the moving households are relatively rich and less affected by both labor and credit conditions, so that their demand for houses does not change much. As a result, house prices fall only by 10–11% as compared to 25% in the Baseline model.

5 Conclusion

The severe financial crisis of 2007-2009 and a deep recession changed the conditions in which households live, and their expectations about the future. I use a quantitative model to evaluate the effects of these events on the housing demand, defaults, and house prices. The model shows that the observed changes in all the conditions combined are associated with a spike in defaults and a decline in house prices that are close to what we have seen in the data.

I use a series of counter-factual exercises to decompose the housing bust into the consequences of individual events. While most events have sizeable contribution to the housing bust, the two stand out. First, tighter credit constraints on mortgages lead to a decline in the housing demand consistent with 12-17% drop in house prices, that is about one half of the observed housing bust. Second, a weak labor market contributes 9-11% to the decline in house prices, that is about 1/3 of the bust. The remaining share is explained mostly by a shift in expectations and by tighter conditions on heloc and credit cards.

A policy experiment demonstrates that mortgage subsidy is a powerful instrument for both stabilizing house prices and preventing mortgage defaults: a subsidy quantified to match the Home Affordable Modification Program prevents a further 9-10% decline in house prices and a 3.5% rise in mortgage delinquencies, that is 1/3 of the observed bust and 1/2 of the observed spike in delinquencies.

For the future work, it is interesting to study how the decomposition of the housing bust differs across the US states or cities that experienced different labor and housing market outcomes during the recession.

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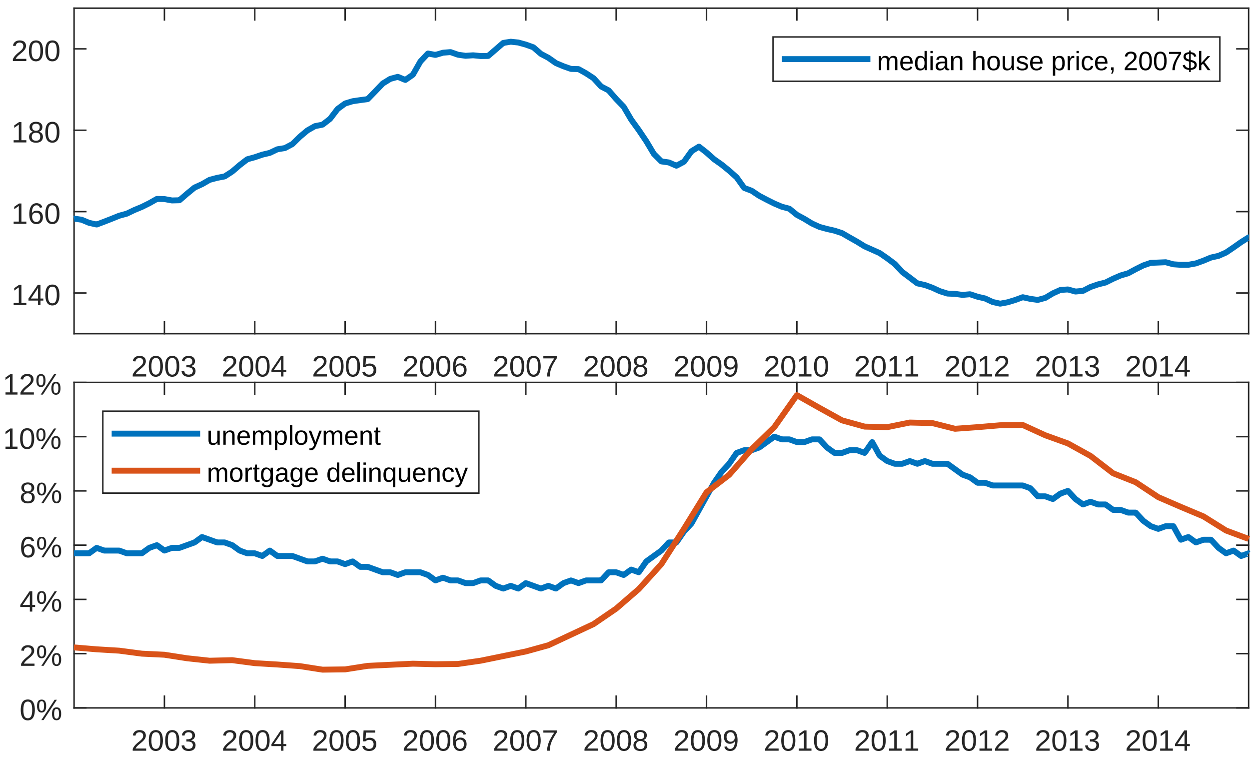
6 Appendix

FIGURE 3: House prices, mortgage delinquencies, and unemployment.



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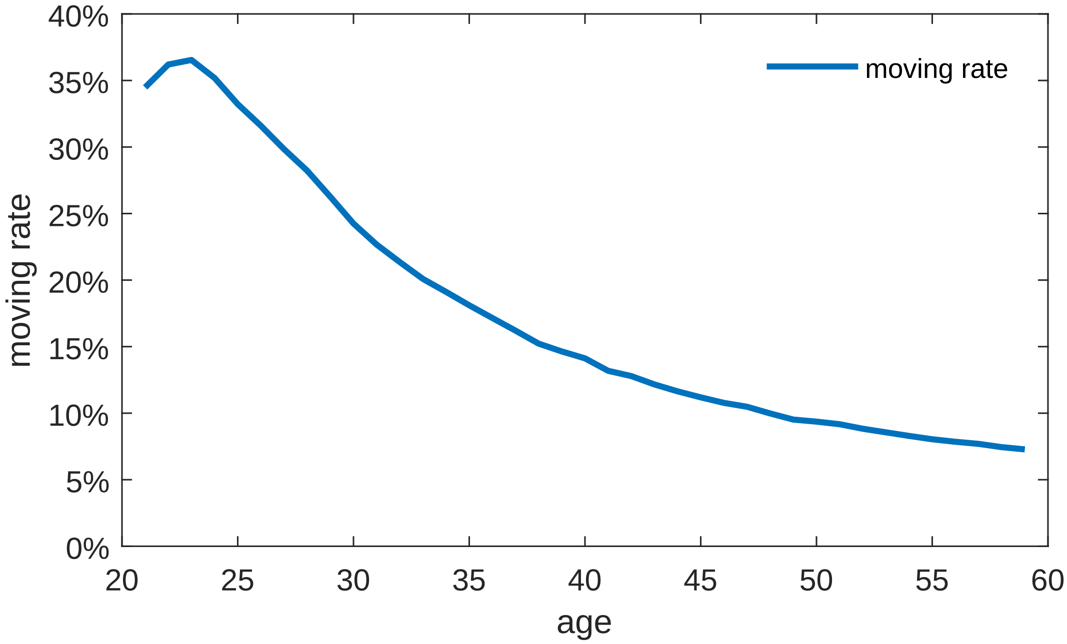
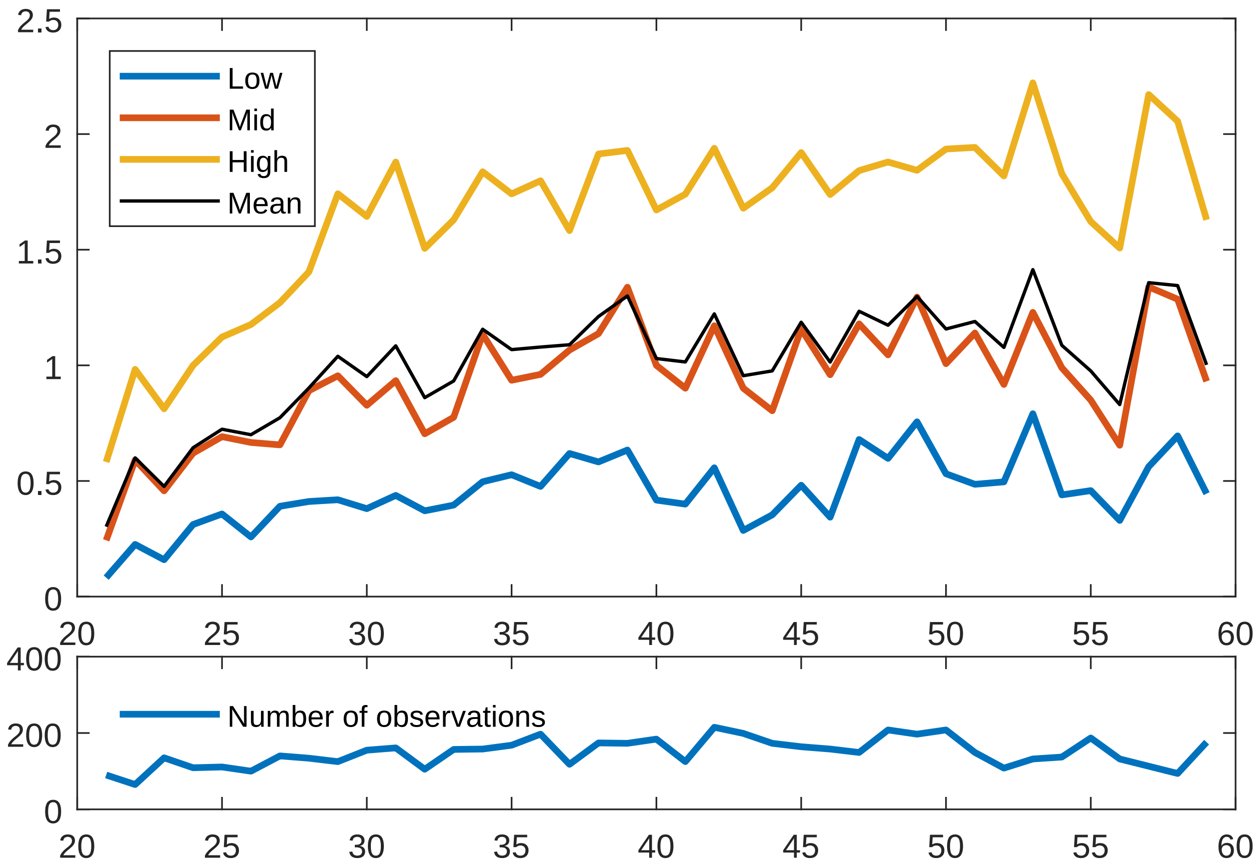
Note: Top panel shows the real median home value, measured in thousands of 2007 US dollars, discounted using CPI. Bottom panel shows the unemployment rate, and the delinquency rate on single-family residential mortgages.
Sources: house price (Zillow), CPI (Fed), delinquencies (Fed), unemployment (Fed)

FIGURE 4: Moving rates by age.



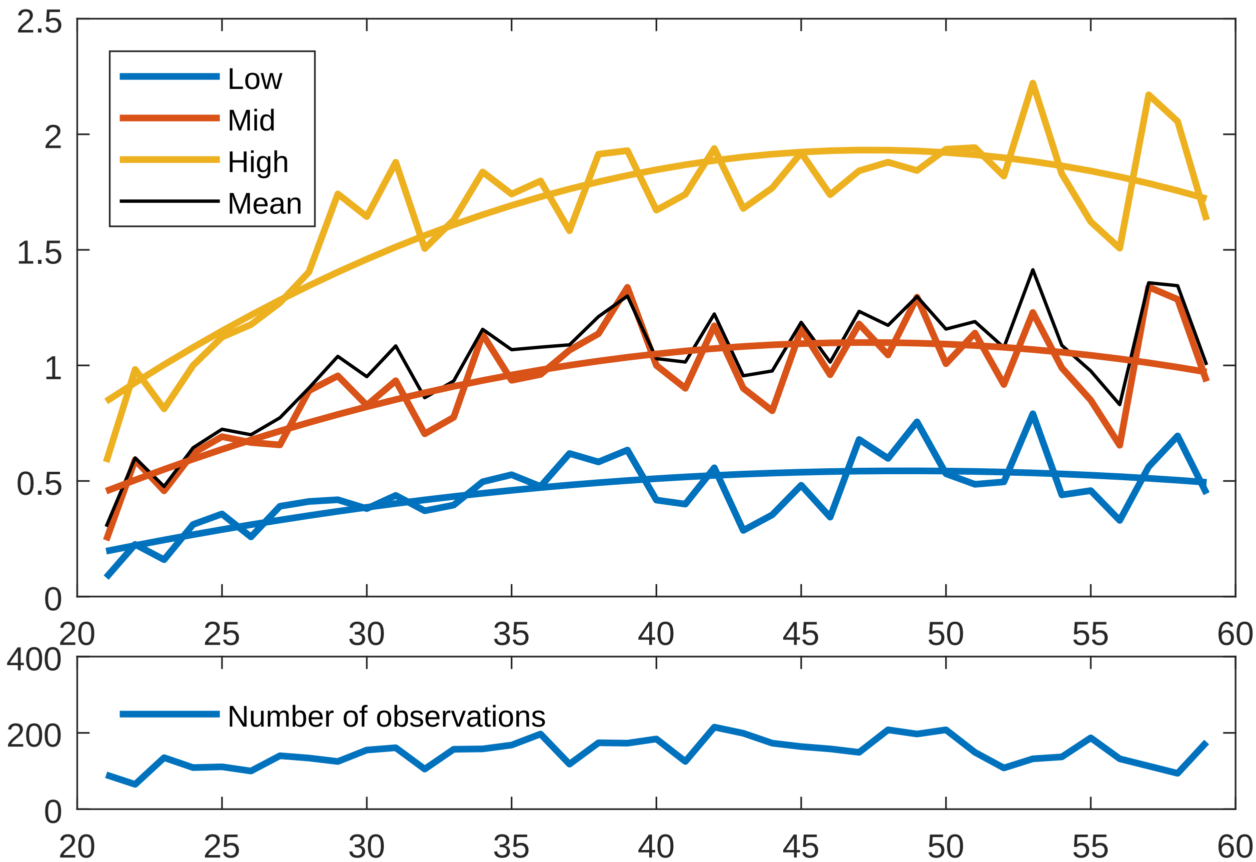
Note: Annual moving rates by age during 2007-2009
Source: 2007-2009 American Community Survey

FIGURE 5: Lifecycle Income Profile: Data.



Note: Labor income in 2007 SCF, relative to the mean. Total gross salary and wage income of the employed only from the Survey of Consumer Finances 2007-09. Within each age group, I split the employed into three income groups of equal size using the SCF sample weights, and compute the mean income.

FIGURE 6: Lifecycle Income Profile: Model.



Note: I fit a quadratic polynomial to each of the three profiles shown in Figure 5.