working paper

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Moving to a Job: The Role of Home Equity, Debt, and Access to Credit

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FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 13-05R January 2014*

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Using individual-level credit reports merged with loan-level data on mortgages, we estimate how mobility relates to home equity and labor market conditions. We control for constant individual-specific traits with fixed effects and find that homeowners with negative home equity move to other metropolitan areas more than other homeowners. We use a dynamic quantitative model of consumption, housing, employment, and mobility to interpret our findings. The utility gain from accepting a higher-paid job in another area is negatively correlated with home equity. The relationship between home equity and mobility in the data is well replicated by the model.

Key words: unemployment, mobility, mortgages, negative equity.
JEL codes: J61, G21, G01, D11, D12.

*First version posted March 2013.

Suggested citation: Demyanyk, Yuliya, Dmytro Hryshko, María José Luengo-Prado, and Bent E. Sørensen, 2014. "Moving to a Job: The Role of Home Equity, Debt, and Access to Credit," Federal Reserve Bank of Cleveland Working Paper No. 1305R.

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1 Introduction

The severe decline in house prices during and after the Great Recession which started in late 2007 may have hampered adjustment in U.S. labor markets by limiting mobility of unemployed workers. Mobility will suffer if unemployed workers are reluctant to leave homes that, with debt exceeding value, cannot be disposed of without injecting cash or defaulting—a pattern referred to as "housing lock-in." If such reluctance keeps workers from moving from depressed areas to areas with available jobs, the Beveridge curve, which depicts the relation between vacancies and joblessness, may shift out. For example, *the Economist*, August 28, 2010, tells this story in an article predicting higher unemployment in the United States (page 68, and leader page 11). However, strong evidence is hard to come by. Using credit report data, we provide evidence that labor market adjustment in the United States is not significantly hampered by households with negative home equity being unable to move to better job prospects and we demonstrate that our estimates are plausible using a theoretical model.[1]

Empirically, we show that the amount of individual-level home equity correlates negatively with mobility, contradicting *the Economist*'s story. We then show that this pattern is theoretically plausible. Using simulated data from a dynamic model, which allows for households endogenously choosing non-durable consumption and housing consumption subject to realistic costs of buying and selling houses, we are able to replicate the patterns in the data. In the model, the unemployed are more likely to move and low home equity predicts higher mobility regardless of employment status. This pattern is stronger in regions with relatively weaker local employment prospects which matches up well with the empirical results. Analyzing the quantitative predictions of the model, it transpires that low-equity (less wealthy) individuals, whether

[1] As pointed out by Sam Schulhofer-Wohl, in a discussion of a draft of this paper, the overall drop in mobility during the crisis, due to home-equity lock-in or other factors, is not large enough to plausibly explain the increase in aggregate unemployment; however, it is still important to quantify if home-equity lock-in contributes to unemployment and it could well be very important in the states that suffered the steepest house price collapses, even if not of first order importance for the aggregate economy.

employed or not, are more likely to accept out-of-region job offers because the utility gain from increased income is higher when wealth is low.

We are able to measure individual-level home equity using a very large dataset from TransUnion—one of the three major credit bureaus in the United States. This dataset contains credit information for borrowers with non-agency securitized mortgages.[2] It is merged with another dataset, the loan-level LoanPerformance (LP) Securities database provided by CoreLogic. The LP database has information on loan and borrower characteristics for about 90 percent of all non-agency securitized mortgage loans. For each loan in the LP dataset, we observe credit scores, debt-to-income ratios, and loan-to-value ratios at the time of loan origination. Also, for each mortgage, we know the location of the property (ZIP code) and its monthly performance after securitization. The LP dataset has an extensive list of loan characteristics but does not contain borrowers' credit information past origination. CoreLogic and TransUnion accurately matched their databases and created a dataset called Consumer Risk Indicators for RMBS.[3] We use this dataset because both mortgage-level and borrower-level attributes are available for each mortgage loan. Importantly, we directly observe the value of the house and the size of the primary loan at loan origination. We then predict home equity assuming the value of the house varies with the average price level in the ZIP code.

The remainder of the paper is organized as follows. Section 2 reviews the extant literature. Section 3 describes our empirical specification and regression results, while Section 4 describes our model, its calibration, and the results of regressions using simulated data. Section 5 concludes.

[2]The government sponsored agencies, Fannie May and Freddie Mac, purchase a very large fraction of U.S. mortgages subject to certain underwriting criteria and a maximum size, called the "conforming limit." Mortgages securitized by these agencies are not in our dataset.

[3]RMBS stands for Residential Mortgage-Backed Securities.

2 Literature Survey

There is a substantial literature on mobility and labor market conditions although only few studies have measures of home equity. Ferreira, Gyourko & Tracy (2010)—updated in Ferreira, Gyourko & Tracy (2011)—study the relationship between mobility and negative equity using the American Housing Survey 1985–2009 and find that people with negative equity in their homes are about 30 percent less likely to move than those with non-negative equity. They argue that, at least in the past, the lock-in effect dominated default-induced mobility. However, Schulhofer-Wohl (2011) questions this finding and argues that the methodology in the previous study is not correct because the authors systematically drop some negative-equity homeowners' moves from the data. The main advantage of our dataset over that of Ferreira et al. (2010) is that we follow individuals and not homes and, therefore, we can control for individual-specific fixed effects. Coulson & Grieco (2013) study the relation between mobility and negative equity using individual-level data from the Panel Study of Income Dynamics (PSID) for 1999–2009 and find no lock-in for owners with negative home equity in the states affected the most by the decline in house prices during the Great Recession. The main advantage of our dataset, compared with the PSID, is that our dataset is large enough that we can control for individual-level heterogeneity using fixed effects. Coulson & Grieco (2013) do not consider local labor market status nor provide a model; however, their empirical results are consistent with ours.

Donovan & Schnure (2011) use data from the American Community Survey 2007–2009 to show that there is a lock-in effect for homeowners who live in areas with large house price declines. The authors, however, find that any lock-in effect emerges almost entirely due to a reduction in within-county mobility. Local mobility is unlikely to be associated with moving to a job; thus, they conclude that housing market lock-in does not cause higher unemployment rates. The American Community Survey does not publish individual-level data so only averages across individuals can be observed. Chan (2001) reports a reduction in household mobility due to falling house prices during 1989–1994 using a sample of mortgages from Chemical Bank which includes equity but lacks the geographical information we have, while Engelhardt (2003), using individual level data—with no information on home equity—from the National Longitudinal Survey of Youth 1985-1996, finds that falling prices do not constrain mobility. Modestino & Dennett (2013) find evidence for housing lock-in using state-level data from the Internal Revenue Service.

Lower geographic out-migration will potentially be a first order problem if it is concentrated within declining local labor markets. Guler & Taskin (2011) find, using MSA-level vacancy and housing data, that increased homeownership during 1990–2005 correlates with higher unemployment in weak local labor markets but not in strong labor markets. They build a model where agents prefer ownership to renting, agents search for jobs and homes to purchase, and owners prefer not to sell and move out of the local area because selling involves a cost. This model can explain why a high level of homeownership may correlate with high unemployment across regions although the model does not include credit constraints or region-specific house prices; rather, it highlights how homeowners' cost of moving may interact with local labor market conditions.

Head & Lloyd-Ellis (2012) build a full general equilibrium model with search for local and non-local jobs as well as housing. They allow for two types of cities, endogenize housing construction and wages, and calibrate their model to high- and low-wage cities. In their model, homeowners are substantially less mobile than renters and have higher unemployment which implies potentially large differences in unemployment between cities but the effect on aggregate unemployment is minor. Our model does not attempt to capture general equilibrium effects but we model housing consumption in more detail.

Barnichon & Figura (2011), using data from the Current Population Survey 1976–2000, show that the efficiency of the aggregate matching function—the typical relation between hiring intensity and the ratio of vacancies to unemployment—has fallen dramatically following the onset of the Great Recession. They do not have access to home equity data but show that local (defined as industry/geography cells) labor market conditions play a significant role in matching. Barnichon, Elsby, Hobijn & Sahin (2010), using data from the Job Openings and Labor Turnover Survey, find that the drop in matching efficiency was particularly pronounced in construction, transportation, trade, and utilities. The decline in house prices and construction activity during the crisis was rather steep in the "sand states" of Arizona, California, Florida, and Nevada. If this concentration in job- and housing-market depressions is associated with low geographical mobility, maybe due to workers being reluctant to sell houses that have lost value, it would partly explain the drop in matching efficiency. Using the Displaced Workers Survey, Schmitt & Warner (2011) confirm that construction workers were displaced more than other workers, but find that displaced construction workers obtain new jobs at the same rate as other displaced workers. Schmitt & Warner (2011) find that displaced workers' frequency of moving to another county or state did not depend on the amount of house-price depreciation in the state, which suggests that underwater mortgages are not a major impediment to mobility of displaced workers.[4] Farber (2012), also using the Displaced Workers Survey, finds no evidence of housing lock-in by comparing homeowners with renters. None of these authors, however, has direct information on home equity, which is the focus of the present paper.

Sterk (2010) estimates a structural Vector Auto-Regressive (VAR) model using aggregate U.S. data. He finds strong effects of innovations in house prices and house sales on the unemployment rate. He then simulates a Dynamic Stochastic General Equilibrium (DSGE) model with a labor market matching function where a certain fraction of job offers can only be accepted if the worker moves. Under the assumption that all workers are owners and have to provide a down payment in order to move, a decline in house prices, which erodes the net worth of workers and their ability to make a down payment, forces workers to decline job offers. Thus, the model implies a causal effect of declining house prices on unemployment.[5] Kaplan & Schulhofer-Wohl (2012)

[4] Geographic mobility helps clear regional disparities in the demand and supply of labor as long as workers on net move from depressed to booming regions; it is not necessary that the displaced individuals themselves are geographically mobile.

[5] Oswald (1997) suggests that homeownership impacts labor market clearing because high

document that interstate migration rates have declined monotonically since 1991 which they interpret as an effect of individuals having better information about non-local job opportunities, combined with a change in the geographical specificity of returns to occupations.[6] Our results are not informative about secular trends but the findings of Kaplan & Schulhofer-Wohl (2012) indicate that geographical mobility in general is less important for aggregate labor market clearing than it once was.

3 Data, regression specifications and results

3.1 Data

We use individual-level credit data from TransUnion, one of the three major credit bureaus in the United States, and mortgage-level data from CoreLogic. We focus on the period of the Great Recession and use the years 2006–2009 so that the moving rates are defined for 2007–2009.

Our dataset, called TransUnion Consumer Risk Indicators for RMBS, contains about 300 credit characteristics for anonymized consumers who had at least one non-agency securitized mortgage at any point in time between September 2001 and August 2011. Using this dataset we know, at the individual-level, what kind of debt and how many accounts consumers had, and how they managed payments on their accounts. We also have, for each consumer, monthly credit scores and updated mailing ZIP codes. This allows us to determine with great certainty if an individual changes his or her residence. Most importantly, this dataset was accurately merged (by the credit bureau) with

costs of selling and buying houses limit geographical mobility. While Green & Hendershott (2001) confirm this result Munch, Rosholm & Svarer (2006) do not find much support for the hypothesis of limited geographical mobility of homeowners using Danish micro data. For further results on the topic see Coulson & Fischer (2002) and Coulson & Fisher (2009). A different, quite voluminous, strand of the mobility literature focuses on the income elasticity of geographical mobility, see Gallin (2004), Bayer & Juessen (2011), and Kennan & Walker (2011).

[6] See also Molloy, Smith & Wozniak (2011) who suggest, looking at regional mobility patterns, that the recent recession and downturn in housing markets played little role in explaining declines of mobility.

the mortgage loan-level LoanPerformance (LP) Securities database provided by CoreLogic, which allows us to measure home equity.[7]

The LP dataset contains information about mortgages at origination and after securitization for over 90 percent of all U.S. non-agency securitized mortgages totalling about 20 million subprime and Alt-A loans and 4.4 million prime loans. For each mortgage in the LP dataset, we observe the borrower's credit score, owner occupancy at origination, and loan-to-value ratios at mortgage origination. In addition, we know the ZIP code for the property location, which is not necessarily the same as an individual's mailing address. Property ZIP codes allow us to merge individual-level data with macro data on house prices and employment in the areas where people live.

Our main cleaning restrictions in TransUnion data are the following. First, we drop observations for which an individual's property ZIP code differs from the mailing (residence) ZIP code at time $t-1$, when the individual's moving decision is made. A discrepancy may indicate either an error, that the owner receives mail elsewhere or, more importantly, that the property is not owner occupied. We further drop observations if the balance-to-limit ratio on all mortgages is either zero or missing. We do so to eliminate borrowers who terminated their loan at time $t-1$, as those are either renters at time $t-1$ or homeowners who paid off their mortgages, for whom considerations of mortgage debt are no longer present when they decide to relocate. Finally, we drop individuals who foreclose in spite of having more than 20 percent equity in their home. This latter restriction eliminates a few individuals for whom measurement error in equity is likely to be substantial. We then randomly select 50 percent of borrowers from the TransUnion-LP dataset for our analysis in order to obtain a more manageable dataset.

[7] The exact matching algorithm is proprietary to the vendors, but it incorporates numerous fields that are available from both databases such as Loan Number, Loan Origination Date, Loan Origination Amount, Property Zip Code and Servicer. Actual borrower names and addresses are used within the algorithm to minimize false positive matches, but the database itself contains only anonymized borrower credit data. The match rate is exceptionally high in comparison to other matched databases studied in the literature. The match rate of open loans in LP data to credit data is currently 93 percent with less than 1 percent false-positive. The match rate for closed loans is currently 73 percent.

Our dataset from TransUnion contains only borrowers with non-agency securitized mortgages. The majority of those mortgages are classified as subprime or Alt-A.[8] Also, as Demyanyk & Van Hemert (2011) show, more than half of those loans are so-called hybrid loans (loans for which interest rate is fixed for two or three years and then starts adjusting, a type of loan non-existent in the prime market) and these loans were short-lived—almost all were in default or prepaid within three years of origination (see, e.g., Demyanyk 2009). These loans, when compared to conventional and prime mortgages, are more likely to have generated negative equity as many were originated with very low down payments during the boom years. We display the distribution of negative equity in this dataset in Figure 1. It is clear from the figure that negative equity by 2007 was prevalent in Michigan and by 2009 in many other states, including Arizona, Florida, Nevada, and West Virginia.

In the combined TransUnion-LP dataset, if a person had an LP loan terminated at time t and moved to some other location at time $t+1$ and did not secure another LP loan at time $t+1$—the majority of cases—we do not have information on that individual's homeownership status and home equity at time $t+1$. Therefore, we normally do not observe a person's moving decisions after a move to another location.[9] For comparison to a representative dataset

[8]LoanPerformance classifies non-agency mortgage-backed securities pools into subprime, Alt-A, and jumbo/prime in the following way. *Subprime* mortgages usually have balances lower than the Freddie/Fannie Mae conforming limit. Loans are originated under expanded credit guidelines. The following characteristics are typical of a subprime pool: more than 75 percent are full-doc loans, very low share of non-owner occupied properties (less than 6 percent), low average FICO credit scores (usually less than 650), more than a half of loans have prepayment penalties, and often are originated to borrowers with impaired credit history. *Prime* loans in the dataset are mainly jumbo mortgages. The pools of these usually contain loans that have balances greater than the Freddie/Fannie Mae conforming loan limit. Mortgages are made under a traditional set of underwriting guidelines to borrowers that have good credit history. *Alt-A* mortgages, generally speaking, are originated to borrowers with good credit histories and scores but under expanded underwriting standards. A typical Alt-A loan would be made for non-owner occupied homes, loans with loan-to-value ratios exceeding 80 percent and no mortgage insurance (or having a "piggy back" second loan at origination), loans made to those who are self-employed, and loans that have high debt to income ratios but are not subprime. Many loans in an Alt-A pool would be no-doc, non-owner occupied, with higher than 620 average FICO scores.

[9]For the population we study, we believe there is no systematic selection based on the amount of equity, our explanatory variable of interest. For example, non-agency securitizers

of borrowers, in Table 1, we display descriptive statistics using the data from another credit bureau, Equifax, which is representative for all consumers with debt but for which we do not have home equity. For robustness, we estimated regressions using Equifax data and house price growth as a proxy for home equity since Equifax does not have information on equity. The results are weaker with smaller and less significant coefficient estimates, although with no indication of a lock-in effect. For brevity, we do not tabulate those results.[10]

We augment borrower-loan level data with a set of macro characteristics for ZIP codes, Core Based Statistical Areas (CBSAs), and states.[11] We use the U.S. ZIP code Database to match CBSAs/States and ZIP codes.[12] CBSA-level and state-level monthly unemployment rates and employment levels are obtained from the Bureau of Labor Statistics.[13] ZIP code-level house price indices (HPI) are obtained from CoreLogic. These indices are calculated using a weighted repeat sales methodology, and they are normalized by setting the index value to 100 for January 2000.

3.2 Variable Definitions

We construct the following dummy variables to capture shocks to households' employment possibilities in the area of their residence. We prefer using dummy variables rather than a continuous measure because this does not impose restrictions such as, e.g., linearity. Let Δu_{rt} denote the change in the annual unemployment rate in region r at time t and Δu_t as its average across all

do not have systematic criterions regarding loan-to-value at origination.

[10]The Equifax Consumer Credit Panel dataset (Equifax), available to us from the Federal Reserve Bank of New York, is an anonymized 5 percent random sample of individuals who have a social security number and use credit in some form in the United States. For a more detailed description of the data see Lee & van der Klaauw (2010).

[11]According to the U.S. Census Bureau: "Core Based Statistical Areas (CBSAs) consist of the county or counties or equivalent entities associated with at least one core (urbanized area or urban cluster) of at least 10,000 people, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties with the counties associated with the core."

[12]http://www.ZIP codes.com/ZIP code-database.asp.

[13]Monthly employment is based on the number of workers who worked during, or received pay for, the pay period including the 12th of the month. Workers on paid vacations and part-time workers also are included.

regions at time t. A shock to the unemployment rate in region r at time t is defined as $\text{Shock}^u_{rt} = \Delta u_{rt} - \Delta u_t$.

Based on the sign of Shock^u_{rt}, we create two dummy variables indicating whether the regional shock is positive or negative (i.e., relatively weak local labor market conditions or relatively strong local labor market conditions). When the regional shock is positive, the dummy variable "Neg. shock" takes the value of one while the dummy variable "Pos. shock" equals one if Shock^u_{rt} takes a negative value. For examining robustness, we define similar dummy variables (with the signs properly adjusted) for changes in local employment and local vacancy rates (vacancy rates are based on help-wanted data from the Conference Board).[14]

After loan origination, homeowners may upgrade or stop maintaining their house, for example due to unemployment; however, the resulting changes in house value are likely to be badly measured because actual appraisals are done only at loan origination. Further, home equity may be endogenous to mobility; for example, homeowners who expect to default may stop maintaining their house while homeowners who plan to sell the house in the market may be extra diligent in making the house attractive. In our regressions, we therefore use predicted home equity; i.e., the home equity the homeowner would hold if he or she took out no further loans and if the value of the house varied with the average price level in the ZIP code.

In the same manner as Demyanyk, Van Hemert & Koijen (2011), we define housing equity for property i at time t as:

$$\%\text{Equity}_{i,t} = 100\left(1 - \frac{\text{Loan}_{i,0}}{\text{Value}_{i,0}} \times \frac{\text{ZIP HPI}_{i,0}}{\text{ZIP HPI}_{i,t}}\right)\%, \tag{1}$$

where we proxy the change in the value of an individual property since origination ($\text{Value}_{i,0}$) by the change in the ZIP code level of house price indices between the origination period ($\text{ZIP HPI}_{i,0}$) and time t ($\text{ZIP HPI}_{i,t}$). Because the variation in predicted home equity comes from exogenous house prices and

[14] In our empirical and theoretical work, we found little difference between regions with relatively high or low unemployment so we did not further explore the functional form by, e.g., allowing for more categories.

the initial loan-to-value ratio is absorbed in the individual-specific fixed effect, we consider the variation in predicted home equity exogenous.[15]

We create dummy variables that group homeowners into four categories based on the estimated amount of home equity. A dummy variable "Equity $\leq -20\%$" equals one if home equity is negative in an amount that exceeds 20 percent of the house value while "Equity $(-20, 0)\%$" equals one if home equity is negative, but numerically less than 20 percent of the house value. Similarly, dummy variables "Equity $[0, 20\%)$" and "Equity $\geq 20\%$" equal one if home equity is positive but low (between 0 and 20 percent) or above 20 percent of the home value, respectively. We use four equity categories for simpler interpretation, but in the Appendix we show similar results using a higher number of categories. We interact each of the dummy variables for CBSA labor market shocks with the equity dummies. As a result, we obtain eight dummy variables. We control for CBSA $\times$ year fixed effects in our empirical analysis and, therefore, out of the eight categories, we omit the two dummies for homeowners with positive but small equity because only three interactions are identified for each labor market shock category in this specification. Table 1 summarizes these dummy variables along with other variables used.

In our analysis, we use several other control variables: foreclosure, the age of the mortgage, and credit scores. We define a "Foreclosure" dummy which equals one if a mortgage (from the LP data) is in foreclosure—a lender initiated a foreclosure process—or in REO (Real-Estate Owned), which means that a lender has taken over the property in year t. "Mortgage age" is the number of months that have passed since mortgage origination divided by 12. "Credit score" is TransUnion's VantageScore which has a range from 501 to 990, and "Subprime score" and "Near prime score" are dummy variables that equal one if the VantageScore takes values below 641 and between 641 and 700, respectively.[16]

[15] Our case for exogeneity is related to the argument in Acemoglu & Johnson (2007) for the exogeneity of instruments similarly generated.

[16] A study by Vantage Score defines individuals with scores below 641 as those with "subprime" scores, and individuals with scores between 641 and 699 as those with "near prime" scores. The study is available here: http://vantagescore.com/research/stability/.

We create a dummy "Investment purpose" that equals one if a consumer bought a property primarily for investment.[17] Most of the loans in the TransUnion dataset are either subprime or Alt-A. About half of those were short-term hybrid mortgages, which are typically very short-lived. We estimate our regressions for subsamples that separate different segments of the market (prime, subprime, and Alt-A) and different type of mortgages (not for investment, neither for investment nor (short-term) hybrid).

3.3 Moving Rates

Table 2 shows that moving rates declined substantially from 2007 to 2009. We present statistics from TransUnion, from an Equifax sample similarly constructed (consumers with positive balances on their mortgages), and from the Current Population Survey (CPS). As shown in the top panel of Table 2, the overall moving rate, computed as a change in ZIP code, declined from approximately 4.3 percent to 3.6 percent for Equifax households, and from about 6.5 percent to 5.8 percent for TransUnion households. The moving rate across CBSAs declined from about 1.5 percent to 1.2 percent in Equifax and from 2.3 percent to 1.8 percent in TransUnion. The moving rate from one state to another declined from 1.1 percent to 0.8 percent in Equifax and from 1.6 percent to 1.1 percent in TransUnion. TransUnion households are predominantly subprime borrowers, which might explain why moving rates differ across the two datasets.[18] In the bottom panel, we tabulate moving rates for homeowners using the CPS. The CPS has much broader coverage than the credit bureaus; for example, it includes very young, highly mobile people who may not yet have a credit history and military personnel as well as owners with zero mortgage balances, which we did not include in our credit bureau samples. Nonetheless,

[17] LoanPerformance contains self-reported information about whether an individual's loan was taken for investment.

[18] The moving rates in Equifax are in line with the national moving rates for homeowners reported, e.g., in Molloy et al. (2011). Higher moving rates in TransUnion could be due to higher risk tolerance of homeowners with non-standard mortgage loans, and higher mobility of more risk tolerant individuals across labor markets (see Dohmen, Jaeger, Falk, Huffman, Sunde & Bonin (2010) for some evidence of the latter).

the CPS, in spite of its very different sampling frame, confirms the temporal patterns of the TransUnion and Equifax samples.

3.4 Regression Specification and Results

We estimate the probability of moving using the following linear probability model:

$$P(M_{it}) = X_{i,t-1}\beta + \delta_j \times \mu_{t-1} + \nu_i + u_{it}, \tag{2}$$

where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise. We focus on mobility between CBSAs because workers typically can move between jobs within a CBSA without moving residence. For robustness we show the results of a few regressions considering interstate mobility. $\delta_j \times \mu_{t-1}$ denotes (lagged) CBSA/state fixed effects interacted with year dummies, and ν_i are individual fixed effects. X is a vector of (lagged) regressors of which the most important are the interactions of home equity with labor market conditions for the area where consumer i resides. We summarize this information in the form of the following dummies: Neg. shock $\times$ equity $\leq -20\%$, Pos. shock $\times$ equity $\leq -20\%$, Neg. shock $\times$ equity $(-20, 0)\%$, Pos. shock $\times$ equity $(-20, 0)\%$, Neg. shock $\times$ equity $\geq 20\%$, and Pos. shock $\times$ equity $\geq 20\%$. Due to the presence of CBSA $\times$ year dummies the interactions Neg. shock $\times$ equity $[0, 20)\%$ and Pos. shock $\times$ equity $[0, 20)\%$ are omitted in order to avoid perfect multicollinearity.

Other regressors include a foreclosure indicator, mortgage age, and credit scores. Explanatory variables are lagged one year for the analysis to reflect credit or labor market conditions before the decision to move is made. We cluster standard errors by ZIP code in the regressions because the variation in home equity, our main variable of interest, comes from house price variation at the ZIP code level.

In the regressions, CBSA $\times$ year dummies remove all effects that are common to all individuals in a given CBSA in a given year; in particular, common local labor market unemployment and house-price shocks. However, homeowners, facing a negative or positive shock to local unemployment, have different mobility rates and different levels of housing equity so that our results are identified from differences between people with different levels of equity in each CBSA in each year. For example, the coefficient to Neg. shock $\times$ equity $\leq -20\%$ is identified from the moving behavior of individuals in a negative shock region whose equity is negative and numerically larger than 20 percent compared to individuals in the same year and region with low positive equity. Because a CBSA faces either a negative or positive shock in a given year, no coefficient of our interactions of interest will be identified from variation across CBSAs or even across good versus bad years within the same CBSA.

3.4.1 Results

Table 4 displays our main results using unemployment rates to measure local labor market conditions. As previously discussed, all regressions include CBSA/state $\times$ year fixed effects and, importantly, individual fixed effects which control for all non time-varying individual traits. (We report the correlation matrices with individual fixed effects removed from each variable in Table 3 and without removing individual fixed effects in the Appendix, Table A-1.) The top eight regressors in the Table 4 are our main variables of interest. The top four regressors are interactions of negative local labor market conditions with the equity dummies while the next four regressors are interactions of positive local labor market conditions with the equity dummies. The left-out dummies identify people with low but positive equity, facing a negative and a positive regional shock, respectively. It should be kept in mind that due to the inclusion of individual fixed effects all variables are identified by changes over time so, for example, the coefficients to the low equity dummies are identified from people who are not in that group throughout.

It is immediately obvious that individuals with very negative equity are not geographically locked in; in fact, they are more likely to move than individuals with low positive equity. From the first column of Table 4, for CBSA moves, not including control variables, we see that compared to the left-out group, individuals with very negative equity positions are 1.6 percent more likely to leave their CBSAs when unemployment increases (relative to U.S. unemployment) and 0.98 percent more likely to leave CBSAs with relatively falling unemployment. When we include individual-level controls, the coefficients for the very negative equity group decrease but remain positive and significant. Clearly, low-equity individuals in this sample, who are underwater with their mortgages, are not locked-in. Mortgage age is highly significant, although this may reflect that very mobile individuals drop out of the sample after moving. Foreclosure is also a highly significant predictor of inter-CBSA mobility. One would expect people to be mobile after foreclosure and we find that many individuals move to new local labor markets following foreclosure, which reinforces the general conclusion that depressed housing markets are not in themselves a source of frictions to geographical labor mobility. Individuals with subprime and, less strongly, near prime scores are more mobile than individuals with prime scores. Because we include individual fixed effects, a more rigorous interpretation of the results is that individuals who have a subprime score but previously had a better score are more mobile than they were before or vice versa. Individuals with a constant subprime score do not contribute to this result due to the individual fixed effects; we show in the Appendix that such individuals are less mobile. The patterns are qualitatively similar for interstate moves, see column (3), although the estimated coefficients to the main variables are lower for interstate moves for individuals with very negative equity. This is intuitive as interstate moves generally involve longer distances and are more costly.

Even though non-agency securitized mortgages are typically subprime or jumbo prime (loans which are larger than the limit at which the Fannie Mae and Freddie Mac agencies purchase mortgages), our sample includes individuals whose mortgages were included in non-agency securities even if they conformed to the agency criteria. It is important to examine this sample in order to verify that our results are not limited to subprime loans (although, given the large amount of these, mobility of subprime borrowers is itself of economic importance). Prime non-jumbo mortgages constitute a small fraction of our dataset, but there are still more than 100,000 observations in this subset so we, in columns (4)-(6), examine if the results hold up. The "no lock-in" result carries over to the prime borrowers even more strongly for regions that are hit by negative labor market shocks: there, individuals with very negative equity (more moderate negative equity) are 2.38 percent (1.69 percent) more likely to move out of CBSAs than individuals with positive home equity (in regions hit by negative shocks there is no significant difference between individuals with moderate or high positive equity). In regions hit by positive shocks, there are no significant differences in mobility between the equity groups. The results point clearly to a lack of housing lock-in for negative equity households. Our interpretation is that the potential costs associated with disposing of an underwater property are outweighed by the benefits of obtaining a job.

The following tables show that our results are robust to the choice of sample. Table 5 focusses solely on CBSA moves and includes individual-level controls in all columns. The first column displays results when we limit our sample to prime jumbo loans. The results demonstrate that the patterns regarding equity are similar for this group, albeit this sample in general consists of individuals who are quite different from those of the subprime or non-jumbo prime sample. In the second column, labeled "Subprime," we report the results for the sample of consumers with subprime mortgages only. The results are very similar to those of the other columns although the higher mobility of individuals with very negative equity is more pronounced. The next column considers individuals with Alt-A loans—the overall mobility patterns are similar to that of subprime borrowers although mobility rates vary a little less strongly with equity for this sample. Mobility increases quite significantly when individuals in this group drop into the subprime category. In the column "Subprime score," we focus on individuals with a credit score below 641 in the first year they are observed in our sample and find results similar to the previous columns and the CBSA results in Table 4, except that the higher mobility of individuals with very negative equity is even more pronounced than for the subprime sample; individuals with high equity in positive shock regions are no more mobile than those in the left-out group. In the column labeled "No invest.," we drop homes purchased for investment. The results are virtually unchanged from the corresponding column of Table 4, column (2). In the last column, (individuals holding) investment loans or (short-term) hybrid loans are dropped. The results are again very similar to the previous ones.

Table 6 examines robustness along other dimensions while focussing on CBSA mobility for the full TransUnion sample. The first column considers only individuals living in non-recourse states where lenders cannot pursue defaulting borrowers for losses beyond the collateral (house) pledged.[19] It may be more tempting for borrowers to foreclose in non-recourse states, although there may be little difference in the results because lenders typically do not pursue defaulted borrowers in recourse states if they do not hold other assets of significance.[20] The results are again similar to those found earlier, except we find relatively higher mobility of individuals with very positive equity in CBSAs with positive labor market shocks. In the second column, we consider all states but use the number of vacancies in the CBSA to measure local labor market conditions. The results are similar to our baseline results as are the results, in the third column, where employment growth in the CBSA, rather than unemployment, is used as the measure of local conditions. Appendix A contains more robustness results: regressions without individual fixed effects, with more equity categories, and using actual equity as reported by CoreLogic rather than predicted equity constructed by us.[21] Our findings are robust to such modifications.

[19]In a non-recourse mortgage state, lenders may not sue borrowers for additional funds beyond the revenue obtained from selling the property pledged as collateral. If the foreclosure sale does not generate enough money to satisfy the loan, the lender must accept the loss.

[20]Ghent & Kudlyak (2011) find higher tendencies to default in non-recourse states for the period 1997-2008. It will take us too far afield to study if this result holds up for our sample period.

[21]CoreLogic matched liens for mortgages found in the LP dataset to subsequent liens taken out on the same property to create a measure of "total debt on a property." They used this measure together with their Automated Valuation Models to estimate subsequent (post mortgage origination) amounts of home equity for each mortgage monthly. Such equity is known as "TrueLTV" equity.

4 The model

In order to interpret our findings, we construct and simulate a model of optimizing consumers. We examine whether the mobility patterns observed in the data can be explained by a model of forward-looking consumers who can lose their job, who choose whether or not to become homeowners, and who face reasonable costs of buying and selling real estate. Low wealth individuals obviously have an incentive to move to regions where jobs are available but would a model, calibrated to data in a typical fashion, predict that this incentive would dominate the disincentive provided by the cost of buying and selling homes? Also, will low-equity movers choose to default on mortgages? We simulate our model and perform regressions on simulated data. If the results using model data match the results using empirical data, we conclude that the patterns in data can be rationalized by our model or, roughly, that nothing more than standard costs of moving and typical gains from moving to a new job are needed in order to explain why there is no lock-in from negative equity.

Our model builds on the work of Díaz & Luengo-Prado (2008), but introduces several non-trivial extensions; in particular, unemployment, mobility across labor markets, and the possibility of default. The model has the following key features: (1) homeownership is a choice for households, (2) households can be employed or unemployed, (3) unemployed households may reduce the duration of unemployment by moving, (4) employed workers may improve their earnings potential if they move elsewhere, (5) moving is costly, particularly for homeowners who face important transaction costs, (6) foreclosure is permitted. Briefly, households have finite life-spans and derive utility from consumption of a nondurable good and housing services which can be obtained in a rental market or through homeownership. House buyers pay a down payment, buyers and sellers pay transactions costs, housing equity above a required down payment can be used as collateral for loans, and foreclosure is allowed. There are no other forms of credit, tax treatment of owner-occupied housing is preferential as in the United States, and households face uninsurable earnings risk and uncertainty arising from house-price variation.

Preferences and demography. Households live for up to T periods and face an exogenous probability of dying each period. During the first R periods of life they receive stochastic labor earnings and from period R on they receive a pension. Consumers display "warm-glow altruism" but houses are liquidated at death so newborns receive only liquid assets.

Households derive utility from nondurable goods and from housing services obtained from either renting or owning a home (households cannot rent and own a home at the same time). One unit of housing stock provides one unit of housing services. The per-period utility of a household of age t is $U(C_t, J_t)$ where C is nondurable consumption and J is housing services. The expected lifetime utility of a household born in period 0 is $E_0 \sum_{t=0}^{T}(1+\rho)^{-t}\left[\zeta_t U(C_t, J_t)+\right.$ $\left.(1-\zeta_t)B(X_t)\right]$, where $\rho \geq 0$ is the time discount rate, ζ_t is the probability of being alive at age t, and X_t is the amount of the bequest.

Market arrangements. A household starts period t with a stock of residential assets, $H_{t-1} \geq 0$, deposits, $A_{t-1} \geq 0$, and collateral debt (mortgage debt and home equity loans), $M_{t-1} \geq 0$. Deposits earn a return r_a and the interest on debt is r_m. A house bought in period t renders services from the beginning of the period. The price of one unit of housing stock (in terms of nondurable consumption) is q_t, while the rental price of one unit of housing stock is r_t^f.

When buying a house, households pay a down payment $\theta q_t H_t$. Therefore, a new mortgage must satisfy the condition $M_t \leq (1-\theta)\, q_t\, H_t$. For homeowners who do not move in a given period, houses serve as collateral for loans (home equity loans) with a maximum loan-to-value ratio (LTV) of $(1-\theta)$. If house prices go down, a homeowner can simply service debt if he or she is not moving. In this case, M_t could be higher than $(1-\theta)\, q_t\, H_t$ as long as $M_t < M_{t-1}$. A homeowner can be "upside-down" (have negative housing equity) for as many periods as the household desires but foreclosure is also an option. This mortgage specification allows us to consider both down payment requirements and home equity loans without the need for modeling specific mortgage contracts or mortgage choice. The specification can be thought of as a flexible mortgage contract with non-costly principal prepayment and home equity extraction.

A fraction κ of the house value is paid when buying a house (interpreted as, e.g., sales tax or search costs). When selling a house, a homeowner loses a fraction χ of the house value (brokerage fees). Houses depreciate at the rate δ_h and homeowners can choose the degree of maintenance. Buying and selling costs are paid if $|H_t/H_{t-1} - 1| > \xi$ which indicates that only homeowners upsizing or downsizing housing services by more than ξ percent pay adjustment costs.[22] Rental housing depreciates at a slightly higher rate than owner-occupied housing ($\delta_h + \varepsilon$, $\varepsilon > 0$) to capture possible moral hazard problems in maintenance. Renters pay no moving costs.

Homeowners sell their houses for various reasons: First, they may want to increase or downsize housing consumption throughout the life cycle. Second, selling the house is the only way to realize capital gains beyond the maximum LTV for home equity loans, so homeowners may sell the house to prop up nondurable consumption after depleting their deposits and maxing out home equity loans. Third, homeowners may sell their house to take a job elsewhere.

Moves can also be the result of foreclosure. When foreclosing, a household must pay a percentage ρ_y of current income and a small percentage ρ_H of the house value during the foreclosure period. Also, the household is forced to rent for one period. There is no additional penalty after that and the household can take a job offer in another location (if received) right away. Homeowners are not allowed to foreclose in the last possible period of life. Lenders have no recourse and cannot pursue unpaid mortgage debt after foreclosure.

Earnings and pensions. Households can be working-age or retired. Working-age households can be employed or unemployed and are subject to household-specific risk in labor earnings. For working-age households, labor earnings, W_t, are the product of permanent income, and two transitory shocks (P_t, ν_t and ϕ_t, respectively): $W_t = P_t \nu_t \phi_t$. ν_t is an idiosyncratic transitory shock with $\log \nu_t \sim N\left(-\sigma_\nu^2/2, \sigma_\nu^2\right)$. $\phi_t = 1$ for employed workers but $\phi_t = \lambda < 1$ for unemployed individuals—i.e., unemployment reduces current income by

[22]We use $\xi = 0.075$ in our baseline calibration. Given our solution method which discretizes housing values relative to permanent income, this assumption prevents households from paying adjustment costs when they are not really moving. For more details regarding the solution method, see footnote 27 and Díaz & Luengo-Prado (2008).

a certain proportion. In turn, permanent income is $P_t = P_{t-1}\gamma_t\epsilon_t\varsigma_t$. This means that permanent income growth, $\Delta \log P_t$, is the sum of a hump-shaped non-stochastic life-cycle component, $\log \gamma_t$, an idiosyncratic permanent shock, $\log \epsilon_t \sim N\left(-\sigma_\epsilon^2/2, \sigma_\epsilon^2\right)$, and an additional factor, $\log \varsigma$, which is positive for currently employed workers who accept a job offer in a different location and zero for everybody else. We do not model geography explicitly but we interpret certain job offers as arriving from a different location. Employment status evolves over time as follows: a fraction a_1 of employed workers becomes unemployed each period. Also, a fraction a_2 of employed workers receives a job offer elsewhere that they may or may not take as it requires selling their current home if they are homeowners. These workers remain employed regardless of the moving decision as does the remaining proportion $1 - a_1 - a_2$. For unemployed workers, a fraction b_1 receives a job offer at their current location and becomes employed next period, a fraction b_2 receives a job offer elsewhere and will be employed next period only if choosing to move, while a fraction $1 - b_1 - b_2$ receives no job offers and remains unemployed with certainty. Unemployment spells may have a duration longer than one period because either an unemployed household receives no job offers or because the offer received was elsewhere and not accepted. Since we do not model geographical locations explicitly, we assume that homeowners believe the region they would be moving to is identical to their current region in terms of the probabilities described above. Also, homeowners who move to another location must sell their current home and rent for one period in the new location before choosing whether to buy or rent again.[23] Retirees receive a pension proportional to permanent earnings in the last period of their working life. That is, for a household born at time 0, $W_t = bP_R$, $\forall t > R$.[24]

House-price uncertainty. House prices are uncertain and, following Li & Yao (2007), house-price appreciation is assumed to be an i.i.d. normal process: $q_t/q_{t-1} - 1 = \varrho_t$, with $\varrho_t \sim N(\mu_\varrho, \sigma_\varrho^2)$. This specification implies that house-

[23]This assumption is imposed for computational reasons. In reality, homeowners do not necessarily dispose of their house in order to accept a job offer in a different labor market.

[24]This simplification is required for computational reasons and is common in the literature. See, for example, Cocco, Gomes & Maenhout (2005).

price shocks are permanent.[25] House-price shocks are common to residents of the same region. In order to keep the model tractable, house prices are a priori identical across locations. Our interpretation is that house price differences in levels are fully compensated by income differentials and we abstract from possible strategic moves to locations with cheaper housing.[26] Our specifications assume no correlation between house price shocks and income shocks—a zero correlation between unemployment and house price shocks allows the model to pinpoint the impact on mobility of either type of shock.[27]

The government. The government taxes income, Y, at the rate τ_y. Imputed housing rents for homeowners are tax-free and interest payments are tax deductible with a deduction percentage τ_m. Taxable income in period t is then $Y_t^\tau = Y_t - \tau_m \, r_m \, M_{t-1}$. Proceeds from taxation finance government expenditures that do not affect households at the margin.

4.1 Calibration

The calibration is constructed to reproduce three statistics from the Survey of Consumer Finances (SCF): the homeownership rate, the median wealth-to-earnings ratio for working-age households, and the median ratio of home value to total wealth for homeowners (70 percent, 1.80, and 0.82, respectively). To match the targets, we use a discount rate of 4 percent, a weight of housing in a Cobb-Douglas utility function of 0.21, and a minimum house size at purchase of 1.6 times permanent income. The general strategy in choosing the

[25] This assumption is common in the literature (e.g., Cocco 2005, Campbell & Cocco 2003), and greatly simplifies the computation of the model by facilitating a renormalization of the household problem with fewer state variables.

[26] Amior & Halket (2011) consider a model which allows for house price levels to vary across cities but do not study mobility.

[27] Given the model assumptions, which include a homothetic utility function, the household problem can be written as a function of three state variables: home values, deposits and mortgages, all relative to permanent income. Because of the adjustment costs, we cannot use techniques that rely on differentiability so we solve a discretized version of the household problem using value function iteration. To keep the problem tractable, we use three grid points (each) to approximate income shock and the house price shocks. The grids for the state variables are denser around the neighborhoods where a significant fraction of households are concentrated. We start by solving the household problem with coarse grids and increase the number of points in each grid until our results do not change significantly.

remaining parameters is to focus whenever possible on empirical evidence for the median household but some parameters are chosen to match additional targets as explained next.

Preferences, endowments and demography. One period in the model corresponds to one calendar year. Households are born at age 24 ($t = 1$), and die at the maximum age of 85 ($t = 61$). The retirement age is 65 ($t = 41$). Survival probabilities are taken from the latest U.S. Vital Statistics (for females 2003), published by the National Center for Health Statistics. The implied fraction of working-age households is 75.6 percent.

We use the non-separable Cobb-Douglas utility function,

$$U(C, J) = \frac{(C^{\alpha} J^{1-\alpha})^{1-\sigma}}{1-\sigma} \tag{3}$$

with curvature $\sigma = 2$.

We assume warm-glow altruism. The utility derived from bequeathing wealth, X_t, is

$$B(X_t) = b \frac{\left(X_t \alpha^{\alpha} [(1-\alpha)/r_t^f]^{1-\alpha}\right)^{1-\sigma}}{1-\sigma},$$

where b measures the strength of the bequest motive, r_t^f is the rental price of housing, and terminal wealth X_t equals the value of the housing stock, after depreciation takes place and adjustment costs are paid, plus financial assets: $X_t = q_t H_t (1-\delta_h)(1-\chi) + A_t$. With Cobb-Douglas utility, inheritors will choose fixed expenditure shares on nondurable consumption and housing services, α and $(1-\alpha)$, which explains the specification for $B(X_t)$. The strength of the bequest motive b is set to 0.6 obtaining a mean bequest-to-income ratio of 2.5 consistent with the evidence in Hendricks (2001).

We follow Cocco et al. (2005) to calibrate labor earnings. Using data from the PSID, these authors estimate the life-cycle profile of income, as well as the variance of permanent and transitory shocks for three different educational groups: no high school, high school, and college. We choose their estimates of the variance of permanent and transitory shocks for households whose head has a high school degree—the typical median household (0.01, and 0.073, respectively).[28] These values are typical in the literature (see Storesletten, Telmer & Yaron 2004). For consistency, we use the estimated growth rate of the non-stochastic life-cycle component of earnings for a household with a high school degree from Cocco et al. (2005). The unemployment replacement rate is set to 60 percent.

We let groups of individuals face different labor markets and house price shocks, and we refer to each group as "a region." In our benchmark case, which we refer to as strong labor markets, employed households remain employed in the same location with 90 percent probability, become unemployed with 5 percent probability, and receive a job offer from another location with 5 percent probability (they can take this offer or reject it, because workers have to pay the cost of relocating in order to accept out-of-region jobs, but remain employed in either case). Unemployed workers receive no job offers with 5 percent probability, become employed in their current location with 85.5 percent probability and receive a job offer from another location (that they can take or not) with 9.5 percent probability (i.e., job offers are 90 percent local, 10 percent from another location). This combination produces an average unemployment rate of roughly 5 percent. The permanent salary increase associated with a job offer in a different location is 5 percent ($\log \varsigma$) for employed workers and zero for unemployed ones.[29] We cannot keep track of actual locations in our stylized model, but we can experiment with the different intensities of job offers (local versus elsewhere) to inform our empirical work regarding the relationship between differential employment opportunities across locations, house price growth and moving decisions. For this reason we also consider regions, which we refer to as weak labor markets, that differ from strong labor market regions only in the proportion of local to non-local job offers for the

[28] Cocco et al. (2005) do not allow for an unemployment shock, so σ_ν^2 is adjusted so that the overall variance of the transitory shock inclusive of this bad shock is equal to their estimate, 0.073.

[29] In a previous version of this paper, non-local offers for the unemployed implied a permanent salary loss. In that case, average moving rates for the unemployed were slightly lower than the rates summarized in Table 10 but otherwise the qualitative conclusions of described in this section were unchanged.

unemployed setting the probability of no offer for unemployed in weak regions to 5 percent, the probability of a local offer to 76 percent, and the probability of a non-local offer to 19 percent (i.e., job offers are 80 percent local, 20 percent from another location).[30]

In our model, retirees face no income uncertainty and we set their pension to 50 percent of permanent income in the last period of working life. Munnell & Soto (2005) find that the median replacement rate for newly retired workers is 42 percent using data from both the Health Retirement Survey and the Social Security Administration. Cocco et al. (2005), using PSID data, report that the ratio of average income for retirees to average income in the last working year before retirement is 68 percent. Our choice is in-between these two numbers.

Market arrangements. The minimum down payment is 5 percent, below the 25 percent average down payment for the period 1963–2001 reported by the Federal Housing Finance Board but in line with pre-crisis terms. The buying cost is 2 percent while the selling cost is 6 percent. The overall moving rate for homeowners in our baseline calibration is roughly 9 percent a year, a bit above the 7 percent figure in TransUnion for 2007–2009. The non-local moving rate for owners is 1 percent, in line with TransUnion figures for interstate moves. The interest rate on deposits, r_a, is set to 4 percent (the average real rate for 1967–2005, as calculated in Díaz & Luengo-Prado 2010), while the interest rate on mortgages is 4.5 percent. Foreclosure entails a one-period 20 percent loss of current income plus an additional 5 percent of the current value of the home.[31] This combination results in a foreclosure rate defined as the number of households foreclosing in a period over the total number of households of 0.7 percent annually, in par with the number calculated using TransUnion data.

There is no age limit on credit availability and in the event of death, houses are liquidated using previous period prices to avoid most negative accidental

[30] Parameters are calibrated to hit targets under the benchmark calibration. When simulating weak labor market regions we keep parameters other than the proportion of local to non-local offers as in the benchmark case.

[31] The latter cost diminishes the incentives to buy a very large house and default in the model.

bequests. A negative bequest is still possible for a homeowner who dies at a young age after a period of house-price depreciation but we do not pass along negative bequests. Foreclosure is not allowed in the last period of life in order to limit strategic foreclosures.

Taxes. We use data on personal income and personal taxes from the National Income and Product Accounts of the Bureau of Economic Analysis as well as information from TAXSIM, the NBER tax calculator to calibrate the income tax rate, τ_y.[32] For the period 1989–2004, personal taxes represent 12.47 percent of personal income in the National Income and Product Accounts. As in Prescott (2004), this number is multiplied by 1.6 to reflect that marginal income tax rates are higher than average rates. The 1.6 number is the mean ratio of marginal income tax rates to average tax rates, based on TAXSIM (for details, see Feenberg & Coutts 1993). The final number is 19.96 percent, which is approximated with $\tau_y = 0.20$. Mortgage payments are fully deductible, $\tau_m = 1$.

House prices. House prices follow the process $q_t = q_{t-1}(1 + \varrho_t)$, where $\varrho_t \sim N(\mu_\varrho, \sigma_\varrho^2)$. $\mu_\varrho = 0$ and $\sigma_\varrho^2 = 0.0131$—as in Li & Yao (2007). ϱ_t is serially uncorrelated and uncorrelated with the income shocks. The housing depreciation/maintenance cost rate for owners, δ_h, is set to 1.5 percent, as estimated in Harding, Rosenthal & Sirmans (2007). Housing depreciation is slightly higher for rental units due to moral hazard, $\delta_h + \varepsilon$, at 1.8 percent.

The rental price is proportional to the house price. In particular:

$$r_t^f = \frac{q_t - E_t\left[\frac{1}{1+(1-\tau_y)r_a}\, q_{t+1}\,(1-(\delta_h+\varepsilon))\right]}{1-\tau_y} = q_t\, \frac{(1-\tau_y)r_a + \delta_h + \varepsilon}{(1-\tau_y)(1+(1-\tau_y)r_a)}, \tag{4}$$

since $E_t[q_{t+1}] = q_t$. This can be interpreted as the user cost for a landlord who is not liquidity constrained, not subject to adjustment costs, and who pays income taxes on rental income. The calibration is consistent with the estimates in Sinai & Souleles (2005), who find the house-price-to-rent ratio capitalizes expected future rents (for more details see Díaz & Luengo-Prado 2010). For

[32]The TAXSIM data is available at `http://www.nber.org/taxsim`.

our benchmark calibration, r_t^f/q_t is roughly 6.1 percent annually. We list all benchmark calibration parameters in Table 7.

Patterns of homeownership and wealth

Figure 2 depicts the evolution of some key variables throughout the life cycle in our baseline calibration. All series are normalized by mean earnings. Panel (a) shows mean labor income (earnings for workers and pensions for retirees) and nondurable consumption. For working-age households, the life-cycle profile for earnings is calibrated to the profile estimated by Cocco et al. (2005) for households with a high school degree. Earnings peak at age 47. For retirees, the pension-replacement ratio is calibrated to be 50 percent of permanent earnings in the last working period. As seen in the figure, our model produces a hump-shaped nondurable consumption profile with a peak around age 56.

Panel (b) in Figure 2 depicts mean wealth and its different components throughout the life cycle. Total wealth is hump-shaped and peaks at ages 64–69, with a value of about 4 times mean earnings in the economy, declining rapidly afterwards. Because there is altruism in the model, total wealth is not zero for those who reach the oldest-possible age. Housing wealth (including collateralized debt) increases until age 51 then stays fairly constant until it begins to decrease at age 72 when the homeownership rate starts to decline.

In the model, households are impatient but prudent and have a clear incentive to pay down their mortgages due to the spread between the rates for mortgages and deposits, even with the tax deductability on mortgage interest payments. However, households have incentives to keep some financial assets at hand as home equity is risky and home equity borrowing is not guaranteed. In fact, just 3.3 percent of households hold no deposits in our baseline simulation, 28.5 percent of households have deposits of less than 15 percent of their annual permanent income, and 30 percent of households hold deposits above 100 percent of their annual permanent income.

The life-cycle profile of moving rates for homeowners is depicted in panel (a) of Figure 3. We focus on moving rates for owners because renters in the model "move" every period as they can adjust housing services without cost. The average moving rate for homeowners is roughly 9 percent and it declines with age. The overall pattern is similar to that in the Equifax data (we cannot use TransUnion because age information is not available to us). This pattern is not surprising because, conditional on receiving a non-local job offer, the total gain from higher salaries or escaping unemployment is lower later in life so older households move less.

Panel (b) of Figure 3 depicts foreclosure rates by age (defined as the total number of households foreclosing out of the total number of households). The average in the model is roughly the same as in TransUnion but the data is depicted along with Equifax which has age information. In both the model and the empirical data foreclosure rates first increase with age and then decrease, the homeownership rate increases with age, and older households have more home equity. The age-profiles for foreclosure in the model and in the data are not exactly alike, though, with lower foreclosure rates in the model initially and higher rates for middle-age households, probably because the model underestimates homeownership for ages 24–45, and overestimates homeownership rates for older cohorts as panel (c) in Figure 3 depicts. The model is calibrated to reproduce the average U.S. homeownership rate only and it seems we need further heterogeneity and/or additional assumptions to exactly replicate the age-homeownership profile. However, this is not the focus of our paper. The aim is to determine if our empirical findings are consistent with a story in which negative equity does not necessarily lock people in a certain location.

Panel (d) of Figure 3 depicts the life-cycle pattern of the median wealth-to-earnings ratio for working-age households, and the median ratio of house value to total wealth for homeowners. The average of these two ratios (along with the average homeownership rate) was the target of our calibration, not the life-cycle profiles. The median wealth-to-earnings ratio in the model—see panel (d)—follows the ratio in the SCF closely. Gross housing wealth as a fraction of total wealth (i.e., the home value divided by total wealth) is lower in the model than in the data for the youngest cohorts, and higher in the model than in the data for the oldest cohorts. The timing of bequests (received early in life in the form of liquid wealth) combined with the lower homeownership rate in the model for ages 24–40 can explain the divergence for the youngest cohorts. For older households, the higher gross housing wealth out of net worth could be due to the limited availability of reverse mortgages in real life (lower collateral debt) or to uncertainty about health expenses in old age which may result in higher liquid savings in the real world, among other things. In any case, the older cohorts are not the focus of our study.

4.2 The moving decision

Our model can be used to study how moving rates in periods with housing appreciation compare to moving rates in periods with housing depreciation and how employment status and job offers affect the decision to move. In particular, we are interested in understanding the potential size of the debated lock-in effect of negative equity in a heterogenous-agent setting. Hryshko, Luengo-Prado & Sorensen (2011) document that moving rates are relatively lower for households with low liquid wealth who become displaced, particularly when houses depreciate, but that study did not consider an endogenous response of workers to job offers.

First, we simulate 54 locations (regions hereafter), of which half have weak labor markets and half have strong labor markets, with 5,000 people each for 250 periods. House-price shocks are common to all individuals in a given region (we approximate the house price process with three shocks) while income and employment shocks are idiosyncratic. To mimic the Great Recession, we set the house-price shock to the lowest value for the last three periods of the simulation (housing depreciation). We use data from the last four periods of the simulations in the tables that follow but results are similar if more periods are included (we use four years of actual data in the TransUnion regressions). We compute predicted equity in simulated data as we did with actual TransUnion data.

4.3 Model-Based Regressions

We restrict the sample to homeowners with positive mortgage balances (before the decision on moving is done) in order to match the selection of the empirical data; further, we designed the model such that movers have to rent for one period which by the restriction just mentioned excludes just-moved from the sample. While this is not literally what happens in our empirical data, movers typically drop out of the empirical sample due to its restriction to house owners with non-agency securitized mortgages, overall we match the sample selection of the empirical data quite tightly. Table 8 shows results from estimating regressions using the simulated data arranged to match the empirical regressions of Table 4 most closely; that is, using the simulated data arranged by region type (local weak or local strong) without relying on individual-level employment status.[33] The results obtained using the model, see column (1), are very similar to the results using empirical data for prime non-jumbo loans—the category which a priori should be the better match. In the simulated data, see column (2), inclusion of the foreclosure dummy lowers the coefficients for the low equity group quite substantially, but this is intuitive as consumers who foreclose in the model are obviously among the ones with very low equity. This result is also present in the TU-LP data but not as clearly. In the model, foreclosure is a very well defined event, but in the data it is not: individuals sometimes stay years in their houses without paying or foreclosing (or at least they did, during the subprime crisis), and some homes in the data do not technically get foreclosed; instead, borrowers can arrange for a short-sale, some modifications from the lender, etc. It is therefore not surprising that the coefficient to foreclosure is much more precisely estimated when using simulated data than when using actual data.

In columns (3) and (4), we consider actual equity. Actual equity is endogenous and forward looking agents who, for instance, plan to default, may choose to run down equity. However, actual equity, to the extent that it is a function of exogenous wage shocks, is a more accurate measure of households'

[33] As in the empirical analysis, all regressions control for individual fixed effects.

equity. It is, therefore, interesting to see how the choice of estimated/actual equity affects the results. As can be seen from column (3), the higher tendency to move when equity is very negative is stronger with actual equity in both weak and strong regions. Such a pattern is consistent with predicted equity being a noisy measure of actual equity because measurement error will bias the absolute value of the coefficient estimates towards zero. In either event, both actual and predicted equity correlate negatively with mobility. Finally, in column (4), we see that this pattern to a very large extent happens through low-equity individuals defaulting. In fact, inclusion of the dummy for default makes the coefficient to very negative equity insignificant in weak regions—this, however, does not imply that low equity individuals do not move!

We expect that the benefit of moving is particularly high for the unemployed and, in Table 9, we explore the propensity of moving for employed versus unemployed workers. This table does not have a match using the empirical data, where individual-level employment status is not observed, but serves to understand the model mechanism.[34] We observe, from columns (1)-(4) which use predicted equity, that unemployed individuals are much more likely to move than employed individuals especially from weak regions where a larger fraction of job-offers are non-local. However, this is not the full story because mobility is relatively higher for individuals with low equity whether the consumer is employed or not. This indicates that low wealth, per se, drives the higher mobility of low-equity consumers. In other words, the relative gain in lifetime utility from accepting an out-of-region job offer is larger for households who lost wealth due to house price declines.[35] Columns (5)-(8) show results using actual equity and the pattern of stronger mobility for negative

[34]All coefficients are relative to employed consumers with low positive equity. There are seven equity-employment status interaction dummies in these regressions as we use individual-level employment status instead of region types while including "region × year" fixed effects.

[35]Low wealth, low home equity and high mobility are characteristics of younger individuals. While the empirical data lack information on age, we are able to estimate how out-of-region mobility relates to home equity and labor market conditions for different ages when using simulated data. We find similar patterns (not reported here for brevity) for different age splits. We therefore conclude that our empirical findings are likely to apply broadly to different age segments of homeowners.

equity individuals still clearly holds across weak and strong labor markets and employed and unemployed individuals. For employed individuals, the coefficient to the dummy for negative equity becomes negative when foreclosure is included implying that it is optimal for such individuals to default before moving but again the pattern of low equity individuals moving relatively more remains. From these regressions, we also learn that the coefficients in Table 8 are a weighted average of the coefficients for unemployed and employed consumers reported in Table 9.

4.4 Model Cross-Tabulations

In order to better understand the mechanisms of the model, we tabulate instructive frequencies by equity categories for strong and weak regions in Table 10. The first column shows the fraction of people, within the strong/weak regions, in each (predicted) equity category. There are no big differences in the proportions of individuals in each equity category since prices evolve similarly in both types of regions by construction. The second column shows that unemployment rates are slightly lower in the weak region. This is because, in our setup, the probability of job loss is the same in each region; however, unemployed workers have a stronger incentive to leave the weak region where job offers arrive less often. The third column further helps understanding the data: agents that are unemployed are significantly more likely to leave strong regions (9.9 percent leave) if their equity is very negative compared to, say, low but positive equity (8.5 percent leave). In the weak region, unemployed agents are more likely to move in general as they receive non-local offers with higher frequency and agents in the two negative equity categories are relatively more likely to move (at 18.3–18.4 percent) than agents with positive equity (17.3–17.9 percent). The fourth column shows, for both strong and weak regions, that the propensity to move for employed people is monotonically declining in equity as captured by our four categories. Therefore, the pattern of overall mobility out of strong or weak regions as a function of equity holdings, with negative-equity individuals being more likely to move, applies to both employed and unemployed individuals—the effect that the more complicated panel regressions with fixed effects picks up. Overall, it appears that the (expected lifetime) utility from the income gain associated with getting a job for the low equity households dominates the cost of moving more often than not. We conclude that a model calibrated in a standard fashion predicts that the benefit of accepting out-of-region job offers will dominate the cost of moving for the unemployed. In utility terms this mechanism is stronger for poorer households which explains why we find the opposite of lock-in.[36]

5 Conclusion

Using a large sample of credit report data matched with mortgage loan-level data, we explore when individuals migrate to another CBSA or state. We relate the likelihood of moving to economic conditions in the area of household residence and to the amount of home equity. We conclude that households with negative home equity are slightly more likely to move from their local labor market (CBSA or state) than households with positive home equity. We formulate and simulate a model, calibrated with reasonable costs of moving, in order to interpret our findings. We find that the model, where the economic benefits of accepting job offers outweigh the costs of moving, matches the estimated empirical patterns well. In conclusion, quantitative modeling predicts that the sharp decline in house prices observed in the United States in the Great Recession should not limit labor mobility and empirical regressions on a very large dataset confirm this prediction.

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[36]We verified the expected pattern that low-equity individuals indeed have less wealth in general, but we do not tabulate this for brevity.

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Table 1: Descriptive Statistics: TransUnion and Equifax.

Variable	TransUnion Mean	TransUnion Std. Dev.	Equifax Mean	Equifax Std. Dev.
Moved CBSA	2.148	14.497	1.320	11.412
Equity ≤–20%	0.045	0.207		
Equity (–20,0)%	0.116	0.321		
Equity [0,20)%	0.339	0.473		
Equity ≥20%	0.499	0.500		
Neg. shock to local unemp. rate	0.548	0.498	0.497	0.500
Neg. shock x equity ≤–20%	0.040	0.197		
Pos. shock x equity ≤–20%	0.005	0.068		
Neg. shock x equity (–20,0)%	0.080	0.271		
Pos. shock x equity (–20,0)%	0.037	0.188		
Neg. shock x equity [0,20)%	0.178	0.382		
Pos. shock x equity [0,20)%	0.162	0.368		
Neg. shock x equity ≥20%	0.250	0.433		
Pos. shock x equity ≥ 20%	0.249	0.433		
Biennial HP gr. ≤–20%	0.204	0.403	0.165	0.371
Biennial HP gr. (–20,0)%	0.348	0.476	0.414	0.492
Biennial HP gr. [0,20)%	0.309	0.462	0.322	0.467
Biennial HP gr. ≥20%	0.138	0.345	0.100	0.300
Neg. shock x HP gr. ≤–20%	0.168	0.374	0.125	0.331
Pos. shock x HP gr. ≤–20%	0.036	0.187	0.04	0.195
Neg. shock x HP gr. (–20,0)%	0.194	0.395	0.198	0.399
Pos. shock x HP gr. (–20,0)%	0.154	0.361	0.215	0.411
Neg. shock x HP gr. [0,20)%	0.136	0.343	0.140	0.347
Pos. shock x HP gr. [0,20)%	0.173	0.378	0.182	0.386
Neg. shock x HP gr. ≥20%	0.050	0.217	0.034	0.181
Pos. shock x HP gr. ≥20%	0.089	0.284	0.066	0.249
Foreclosure dummy	0.067	0.251	0.012	0.109
Mortgage age	2.001	1.564	3.177	1.826
Subprime score	0.205	0.404	0.195	0.396
Near prime score	0.136	0.343	0.091	0.288
Prime mortgage	0.197	0.398		
Subprime mortgage	0.453	0.498		
Alt-A mortgage	0.350	0.477		
Investment purpose	0.028	0.164		
Short-term Hybrid	0.240	0.427		
Neg. shock to local vacancy rate	0.599	0.490		

Note: "Moved CBSA" is a dummy variable that equals 100 if an individual moved to another CBSA since the previous year. "Neg. shock (to local unemp. rate)" is a dummy variable that equals one if the difference between the annual change in regional unemployment rate and the national average is positive. "Neg. shock to local vacancy rate" is calculated similarly using the vacancy rate instead of unemployment rate. "Foreclosure dummy" for the TransUnion sample equals one if a borrower at time t is in foreclosure (source: CoreLogic). This variable in the Equifax sample equals one if a consumer had at least one property in foreclosure during the last 24 months from t. "Credit Score" in TransUnion data is a VantageScore. In Equifax, this variable is called RiskScore. "Subprime score" and "Near prime" score are dummy variables that equal one if the credit score is less than 641 in TransUnion and less than 661 in Equifax. Prime, Subprime, and Alt-A mortgage are dummy variables that equal one if a mortgage is of a certain risk type, based on the CoreLogic classification. "Mortgage age" is the number of months since mortgage origination. Equity measures were calculated by the authors using loan-to-value ratios at mortgage origination from LoanPerformance adjusted for the subsequent house-price appreciation at the ZIP code level (using house price index from CoreLogic). "Investment purpose" is a dummy variable that equals one if a mortgage was originated primarily for investment purposes. Short-term hybrid is a dummy variable that equals one if a mortgage is 2/28 or 3/27 hybrid. These two variables are from CoreLogic. All listed variables except for moving rates have been lagged one year for the analysis.

Table 2: Moving Rates (percent).

Year	**ZIP**	**CBSA**	**State**
	TransUnion		
2007	6.47	2.31	1.55
2008	7.63	2.31	1.38
2009	5.78	1.77	1.10
Overall	6.63	2.15	1.35
	Equifax, FRBNY CCP		
2007	4.34	1.52	1.13
2008	3.93	1.44	1.06
2009	3.56	1.15	0.81
Overall	3.93	1.37	1.00
	Current Population Survey		
Year	**County**	**MSA**	**State**
2007	2.55	2.41	1.16
2008	2.07	1.95	0.96
2009	1.89	1.75	0.91
Overall	2.17	2.04	1.01

Note: The table shows moving rates calculated from the two credit bureau datasets and from the Current Population Survey (CPS). The first column shows the fraction of homeowners who moved to a different ZIP code between years $t-1$ and t except, for the CPS, the first column shows the fraction of homeowners in year t who moved from one county to another because the ZIP code identifier is not available in this dataset. The second column shows the fraction of homeowners who moved to a different CBSA between years $t-1$ and t. The third column shows moving rates from from one state to another. The rates have been multiplied by 100.

Table 3: Correlation matrix. TransUnion.
CBSA × Year and Individual Fixed Effects removed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Moved MSA	1.000									
(2) Neg. shock times eq. $\leq$–20%	0.028	1.000								
(3) Pos. shock times eq. $\leq$–20%	-0.004	-0.069	1.000							
(4) Neg. shock times eq. (–20,0)%	0.005	-0.254	-0.065	1.000						
(5) Pos. shock times eq. (–20,0)%	-0.011	-0.149	-0.163	-0.097	1.000					
(6) Neg. shock times eq. [0,20)%	0.000	-0.159	-0.047	-0.242	-0.101	1.000				
(7) Pos. shock times eq. [0,20)%	-0.020	-0.237	-0.034	-0.187	-0.166	-0.217	1.000			
(8) Neg. shock times eq. >20%	0.010	0.095	-0.002	-0.116	-0.046	-0.368	-0.074	1.000		
(9) Pos. shock times eq. >20%	-0.010	-0.136	0.005	-0.067	0.002	-0.117	-0.194	-0.490	1.000	
(10) Foreclosed	0.053	0.158	0.006	0.063	-0.013	-0.004	-0.102	-0.001	-0.072	1.000
(11) Mortg. age	-0.016	0.076	0.066	0.064	0.127	-0.007	0.042	-0.110	-0.131	0.027
(12) Subprime score	0.011	0.074	0.017	0.006	0.055	-0.023	0.037	-0.088	-0.020	0.122
(13) Near prime score	0.001	-0.026	-0.011	-0.015	0.016	0.010	0.062	-0.049	0.007	-0.012
(14) Log score	-0.018	-0.069	-0.001	0.001	-0.080	0.007	-0.110	0.165	0.028	-0.137
(15) Equity$\leq$–20%	0.026	0.935	0.289	-0.267	-0.201	-0.169	-0.240	0.091	-0.129	0.154
(16) Equity (–20,0)%	-0.001	-0.308	-0.148	0.833	0.470	-0.271	-0.258	-0.129	-0.058	0.049
(17) Neg. shock	0.028	0.360	-0.128	0.247	-0.280	0.304	-0.517	0.447	-0.614	0.135
(18) House Price Gr $\leq$–20%	0.054	-0.250	-0.012	-0.104	0.051	-0.033	0.168	-0.047	0.190	-0.010
(19) House Price Gr (–20,0)%	0.017	0.103	-0.044	0.005	-0.119	0.006	-0.113	0.098	-0.001	-0.005
(20) House Price Gr [0,20)%	-0.033	0.135	0.049	0.075	0.031	0.004	-0.081	-0.027	-0.105	0.023
(21) House Price Gr >20%	-0.061	0.030	0.017	0.042	0.060	0.036	0.033	-0.039	-0.136	-0.010

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(12) Subprime score	0.145	1.000								
(13) Near prime score	0.000	-0.393	1.000							
(14) Log score	-0.125	-0.691	-0.123	1.000						
(15) Equity$\leq$–20%	0.097	0.077	-0.028	-0.066	1.000					
(16) Equity (–20,0)%	0.128	0.036	-0.004	-0.043	-0.348	1.000				
(17) Neg. shock	-0.002	-0.041	-0.056	0.096	0.300	0.063	1.000			
(18) House Price Gr $\leq$–20%	-0.083	0.047	0.046	-0.098	-0.244	-0.064	-0.288	1.000		
(19) House Price Gr (–20,0)%	-0.138	-0.080	-0.028	0.112	0.083	-0.061	0.147	-0.474	1.000	
(20) House Price Gr [0,20)%	0.069	0.000	-0.018	0.010	0.147	0.084	0.115	-0.388	-0.403	1.000
(21) House Price Gr >20%	0.235	0.049	-0.001	-0.036	0.035	0.071	0.048	-0.236	-0.246	-0.201

Table 4: TransUnion, years 2007–2009.
Probability of moving to another location.

	All loans			Prime non-jumbo loans		
	CBSA (1)	CBSA (2)	State (3)	CBSA (4)	CBSA (5)	State (6)
Neg. shock × equity$\leq -20\%$	1.60***	1.25***	0.49***	2.70***	2.38***	0.96**
	(19.47)	(15.71)	(10.11)	(3.48)	(3.02)	(1.97)
Neg. shock × equity$(-20, 0]\%$	0.52***	0.38***	0.18***	1.82***	1.69***	0.63**
	(11.99)	(8.80)	(6.10)	(4.00)	(3.73)	(1.99)
Neg. shock × equity$[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock × equity$\geq 20\%$	–0.17***	–0.12***	–0.09***	0.12	0.06	0.15
	(–4.62)	(–3.28)	(–3.33)	(0.38)	(0.18)	(0.59)
Pos. shock × equity$\leq -20\%$	0.98***	0.72***	0.52***	0.75	0.59	2.00
	(6.57)	(–4.87)	(3.07)	(0.44)	(0.34)	(0.38)
Pos. shock × equity$(-20, 0]\%$	0.55***	0.42***	0.26***	0.1	0.01	0.05
	(9.52)	(7.23)	(5.09)	(0.16)	(0.02)	(0.08)
Pos. shock × equity$[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Pos. shock × equity$\geq 20\%$	0.06	0.07	0.07**	–0.66	–0.61	0.28
	(1.36)	(1.48)	(2.02)	(–1.61)	(–1.49)	(0.79)
Foreclosure dummy		1.85***	0.94***		2.74***	1.88**
		(26.36)	(20.29)		(2.96)	(2.52)
Mortgage age		0.73***	0.54***		3.27	3.73
		(11.13)	(9.93)		(0.65)	(0.76)
Subprime score		0.45***	0.19***		0.19	0.05
		(10.75)	(6.42)		(0.37)	(0.12)
Near prime score		0.19***	0.08***		0.26	0.12
		(5.57)	(3.15)		(0.62)	(0.33)
CBSA x year effects	Y	Y	N	Y	Y	N
State x year effects	N	N	Y	N	N	Y
Individual effects	Y	Y	Y	Y	Y	Y
No. obs.	6,581,245	6,581,245	6,531,658	105,886	105,886	105,087
No. clusters	5631	5631	5598	5130	5130	5094
No. indiv.	3,032,070	3,032,070	3,007,744	47,537	47,537	47,150

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment growth in a CBSA/state and the four equity dummies are variables reflecting the extent of mortgage equity at time $t-1$. See Section 3.2 for a detailed variable description. $\delta_j \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects, and ν_i are individual fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table 5: TransUnion, years 2007–2009. Probability of moving to another CBSA. Robustness I

	Prime jumbo	Subprime	Alt-A	Subprime score	No invest.	No invest. Nor hybrid
Neg. shock × equity $\leq -20\%$	0.76***	1.39***	1.24***	1.66***	1.26***	1.21***
	(3.52)	(13.05)	(10.85)	(9.15)	(15.50)	(13.73)
Neg. shock × equity $(-20, 0]\%$	0.55***	0.43***	0.29***	0.43***	0.38***	0.36***
	(4.69)	(7.17)	(4.33)	(4.33)	(8.71)	(7.48)
Neg. shock × equity$[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock × equity $\geq 20\%$	–0.31***	0.05	–0.13**	0.04	–0.11***	–0.14***
	(–3.95)	(0.88)	(–2.05)	(0.44)	(–3.01)	(–3.59)
Pos. shock × equity $\leq -20\%$	0.99*	0.83***	0.63***	0.85***	0.72***	0.68***
	(1.68)	(4.25)	(2.79)	(3.00)	(4.80)	(3.98)
Pos. shock × equity $(-20, 0]\%$	0.52**	0.48***	0.38***	0.49***	0.42***	0.41***
	(2.45)	(6.55)	(3.78)	(4.58)	(7.11)	(5.99)
Pos. shock × equity$[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Pos. shock × equity $\geq 20\%$	0.07	0.11*	0.15*	0.10	0.06	0.00
	(0.61)	(1.89)	(1.91)	(1.19)	(1.35)	(0.06)
Foreclosure dummy	2.79***	1.68***	2.21***	1.21***	1.86***	2.04***
	(7.84)	(21.08)	(18.14)	(12.82)	(26.31)	(23.50)
Mortgage age	0.96***	0.40***	0.75***	0.59***	0.80***	0.81***
	(7.02)	(3.92)	(6.71)	(3.81)	(11.78)	(10.61)
Subprime score	0.49*	0.45***	0.55***	–0.21**	0.45***	0.42***
	(1.88)	(9.34)	(6.73)	(–1.99)	(10.57)	(8.62)
Near prime score	0.19	0.18***	0.13**	0.08	0.19***	0.18***
	(1.01)	(4.46)	(2.08)	(0.74)	(5.59)	(4.80)
CBSA × year effects	Y	Y	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y	Y	Y
No. obs.	1,182,901	2,986,358	2,306,100	1,114,358	6,396,953	4,835,950
No. clusters	5366	5628	5629	5628	5631	5630
No. indiv.	508,709	1,443,513	1,047,187	560,593	2,950,033	2,140,217

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment growth in a CBSA and the four equity measures are dummy variables reflecting the extent of mortgage equity at time $t-1$. $\delta_j \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects, and ν_i are individual fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10]% level. Column "No invest" drops individuals who are identified by CoreLogic as buying property primarily for investment purposes. Column "No invest. nor Hybrid" further drops holders of "hybrid" loans (loans with an initial fixed rate which adjusts annually after the initial period). Column "Subprime" refers to individuals whose loans are labeled so by CoreLogic, while "Subprime score" refers to individuals with a VantageScore less than 641. Column "Alt-A" includes individuals who hold Alt-A loans, of which many are held by investors. "Prime" refers to individuals who hold prime loans, the majority of which are jumbo loans.

Table 6: TransUnion, years 2007–2009. Probability of moving to another CBSA. Robustness II

	Non-recourse states	All states, vacancy rates	All states, empl. growth
Neg. shock × equity$\leq -20\%$	1.09***	1.11***	1.28***
	(10.74)	(12.82)	(13.45)
Neg. shock × equity$(-20, 0]\%$	0.30***	0.33***	0.38***
	(5.20)	(7.67)	(7.66)
Neg. shock × equity$[0, 20)\%$	excluded group	excluded group	excluded group
Neg. shock × equity$\geq 20\%$	–0.14***	–0.11***	–0.13***
	(–2.73)	(–3.09)	(–3.07)
Pos. shock × equity$\leq -20\%$	0.69**	0.68***	1.09***
	(2.22)	(5.02)	(10.53)
Pos. shock × equity$(-20, 0]\%$	0.41**	0.30***	0.43***
	(2.53)	(4.90)	(9.08)
Pos. shock × equity$[0, 20)\%$	excluded group	excluded group	excluded group
Pos. shock × equity$\geq 20\%$	0.37***	0.04	0.01
	(4.23)	(0.88)	(0.35)
Foreclosure dummy	1.85***	1.44***	1.85***
	(16.58)	(21.52)	(26.42)
Mortgage age	0.71***	0.63***	0.72***
	(7.51)	(9.39)	(11.06)
Subprime score	0.68***	0.38***	0.46***
	(9.19)	(8.63)	(10.80)
Near prime score	0.27***	0.17***	0.19***
	(4.48)	(4.85)	(5.62)
CBSA × year effects	Y	Y	Y
Individual effects	Y	Y	Y
No. obs.	2,816,802	5,246,225	6,581,245
No. clusters	1655	3976	5631
No. indiv.	1,285,893	2,409,507	3,032,070

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to CBSA vacancy rate (second column) or employment growth (third column); the four equity measures are dummy variables reflecting the extent of mortgage equity at time $t-1$. $\delta_j \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects, and ν_i are individual fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10]% level. Column "Non-recourse states" reports regressions from the subsample of individuals living in states where lenders typically cannot pursue claims on assets other than the collateral pledged. Columns labeled "All states, vacancy rates" and "All states, empl. growth" use the full TransUnion sample but CBSA vacancy rates and employment growth rates, respectively, for construction of the labor market shocks.

Table 7: Benchmark Calibration Parameters.

Preferences	
	Cobb-Douglas utility; .21 weight for housing.
	Discount rate 4.0 percent; curvature of utility 2.
Demographics	
	One period is one year.
	Households are born at 24, retire at 65 and die at 86 the latest.
	Mortality shocks: U.S. vital statistics (females), 2003.
Income	
	Overall variance of permanent (transitory) shocks 0.01 (0.073).
	Unemployed: 60 percent replacement rate.
	Local job offer probability for strong (weak) region 85.5 percent (76 percent).
	Elsewhere job offer probability 9.5 percent, no permanent income decrease.
	No job offer probability 5 percent.
	Employed:
	Unemployment shock probability 5 percent.
	Elsewhere job offer probability 5 percent, 5 percent permanent income increase.
	No change probability, 90 percent.
	Pension: 50 percent of last working period permanent income.
Interest rates	
	4% for deposits; 4.5 percent for mortgages.
	No uncertainty.
Housing Market	
	Down payment 5 percent.
	Buying (selling) cost 2 percent (6 percent).
	Foreclosure: income (house) one-time cost 20 percent (5 percent).
Taxes	
	Proportional taxation.
	Income tax rate 20 percent (TAXSIM); mortgage interest fully deductible.
House Prices	
	Average real appreciation 0; variance 0.0131.
	Housing depreciation: owners, 1.5 percent; renters, 1.8 percent
	Rent-to-price ratio 6.1 percent.
Other	
	No income and house-price correlation.
	Warm-glow bequest motive.

Table 8: Moving in the Model. Equity and Different Region Types. Owners with Positive Mortgage Balance, Aged 25–60.

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × equity $\leq -20\%$	2.79***	1.18***	6.83***	–0.22
	(19.64)	(11.12)	(16.02)	(–0.54)
Local Weak × equity $(-20, 0)\%$	1.43***	0.73***	2.79***	–0.05
	(18.62)	(11.17)	(25.26)	(–0.37)
Local Weak × equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × equity $\geq 20\%$	–1.15***	–1.14***	–1.19***	–0.54***
	(–9.62)	(–9.38)	(–9.42)	(–4.57)
Local Strong × equity $\leq -20\%$	1.97***	0.35***	5.97***	–1.07**
	(13.67)	(3.51)	(13.21)	(–2.33)
Local Strong × equity $(-20, 0)\%$	0.96***	0.24***	2.19***	–0.66***
	(13.85)	(4.57)	(17.62)	(–4.69)
Local Strong × equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × equity $\geq 20\%$	–0.51***	–0.49***	–1.09***	–0.44***
	(–6.73)	(–6.37)	(–10.28)	(–4.33)
Foreclosure dummy		5.90***		6.35***
		(33.00)		(34.64)
N	880946	880946	880946	880946

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, X is a vector of (lagged) regressors, $\delta_j \times \mu_{t-1}$ is the product of (lagged) region fixed effects and time fixed effects and ν_i are individual fixed effects. Robust standard errors are clustered by region. *** (**) [*] significant at the 1 (5) [10] percent level. Local weak regions and local strong regions differ in the intensity of local versus non-local job offers (80 percent and 90 percent, respectively). Results are for a Great Recession Calibration with house prices declining for three consecutive periods.

TABLE 9: MOVING IN THE MODEL. EQUITY.
OWNERS WITH POSITIVE MORTGAGE BALANCE, AGED 25–60.

	PREDICTED EQUITY				ACTUAL EQUITY			
	STRONG REGIONS		WEAK REGIONS		STRONG REGIONS		WEAK REGIONS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployed × equity $< -20\%$	9.83***	8.35***	18.03***	16.22***	13.88***	7.65***	21.87***	14.24***
	(12.97)	(10.75)	(24.99)	(21.16)	(7.47)	(4.31)	(8.07)	(5.43)
Unemployed × equity $(-20, 0)\%$	8.62***	8.10***	16.68***	16.00***	6.35***	4.27***	15.76***	12.91***
	(19.76)	(18.26)	(24.19)	(23.27)	(8.20)	(5.60)	(13.49)	(11.39)
Unemployed × equity $> [0, 20)\%$	5.91***	6.28***	13.16***	13.48***	6.84***	6.99***	13.61***	13.55***
	(18.69)	(19.89)	(26.87)	(27.69)	(11.84)	(12.00)	(19.89)	(20.24)
Unemployed × equity $[0, 20)\%$	6.78***	6.86***	14.08***	14.16***	6.61***	7.27***	14.22***	14.95***
	(24.97)	(24.86)	(38.34)	(37.23)	(27.76)	(30.80)	(49.41)	(50.73)
Employed × equity $< -20\%$	1.77***	0.22***	2.23***	0.47***	6.06***	–0.56	6.75***	–1.02**
	(12.25)	(3.88)	(15.56)	(5.86)	(13.95)	(–1.40)	(17.55)	(–2.60)
Employed × equity $(-20, 0)\%$	0.85***	0.16***	1.11***	0.34***	2.51***	–0.18	2.87***	–0.27*
	(12.28)	(3.60)	(18.88)	(6.23)	(18.77)	(–1.43)	(22.07)	(–1.90)
Employed × equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Employed × equity $> 20\%$	–0.56***	–0.53***	–1.08***	–1.05***	–0.91***	–0.28***	–1.07***	–0.36***
	(–7.31)	(–6.83)	(–10.11)	(–9.79)	(–9.50)	(–3.30)	(–9.68)	(–3.82)
Foreclosure dummy		5.68***		6.49***		5.96***		6.99***
		(25.55)		(24.30)		(28.49)		(24.99)
N	444769	444769	436177	436177	444769	444769	436177	436177

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, X is a vector of (lagged) regressors, $\delta_j \times \mu_{t-1}$ is the product of (lagged) region fixed effects and time fixed effects and ν_i are individual fixed effects. Robust standard errors are clustered by region. *** (**) [*] significant at the 1 (5) [10] percent level. Local weak regions and local strong regions differ in the intensity of local versus non-local job offers (80 percent and 90 percent, respectively). Results are for a Great Recession Calibration with house prices declining for three consecutive periods.

Table 10: Frequencies of Equity, Unemployment and Mobility in the Model. Owners, Aged 25–60.

Local Strong Regions					
Predicted	Frequency	Unemployed	% Moving		
equity	%	%	Unemployed	Employed	All
	(1)	(2)	(3)	(4)	(5)
Equity $\leq -20\%$	11.4	5.3	9.9	0.8	1.3
Equity $(-20, 0)\%$	14.0	5.0	9.8	0.6	1.1
Equity $[0, 20)\%$	23.6	5.0	8.5	0.3	0.7
Equity $\geq 20\%$	51.0	4.9	8.9	0.1	0.5
N	444769	22088			
Local Weak Regions					
Predicted	Frequency	Unemployed	% Moving		
equity	%	%	Unemployed	Employed	All
Equity $\leq -20\%$	11.3	5.2	18.3	0.8	1.7
Equity $(-20, 0)\%$	13.9	5.0	18.4	0.6	1.5
Equity $[0, 20)\%$	23.3	4.6	17.3	0.3	1.0
Equity $\geq 20\%$	51.5	4.5	17.9	0.1	0.9
N	436177	20399			

Notes: Local weak regions and local strong regions differ in the intensity of local versus non-local job offers (80 percent and 90 percent, respectively). We pool data from all individuals and all four periods of simulated data used in the regressions reported in Table 9. Employment status is defined year-by-year so individuals may move between the categories.

Figure 1: Distribution of Negative Equity by State.

(Percentage of individuals with negative equity in TransUnion)

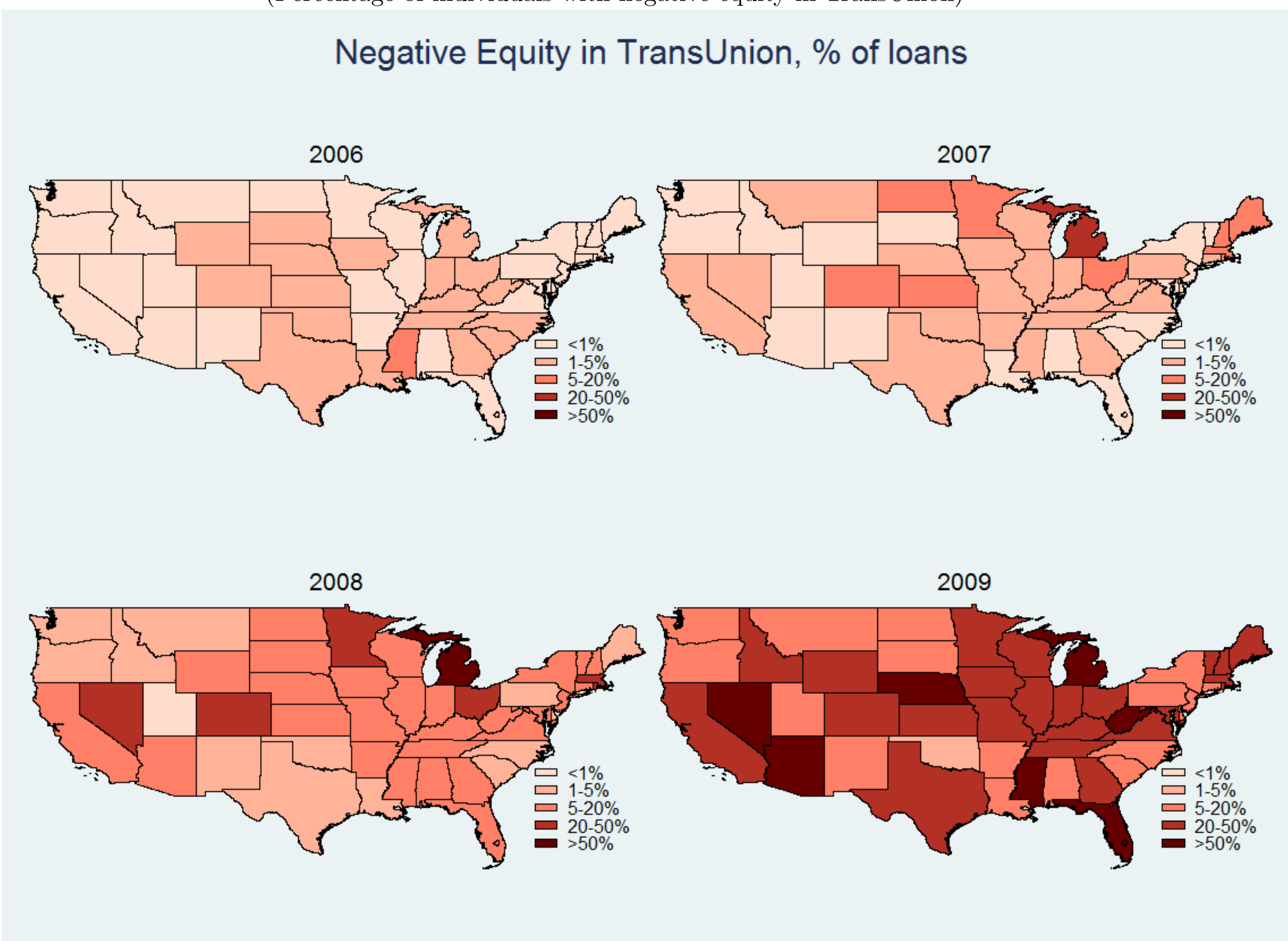
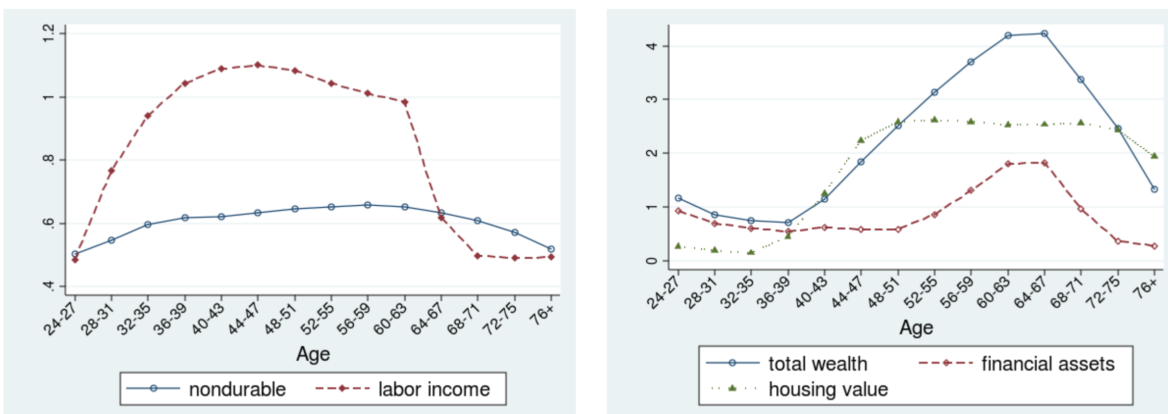


Figure 2: Life-cycle Profiles. The Benchmark Case.

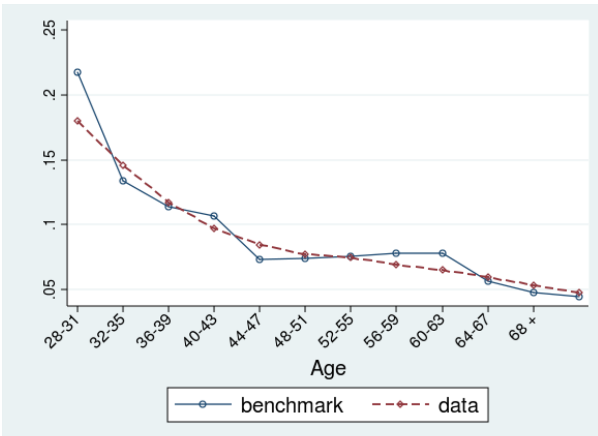


(a) Income and Consumption

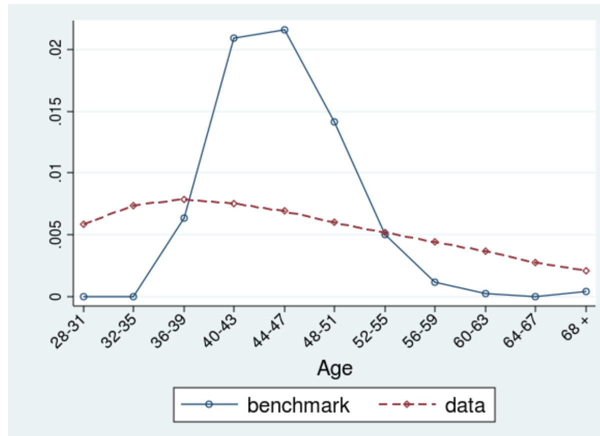
(b) Wealth

Figure 3: The Benchmark and the Data.

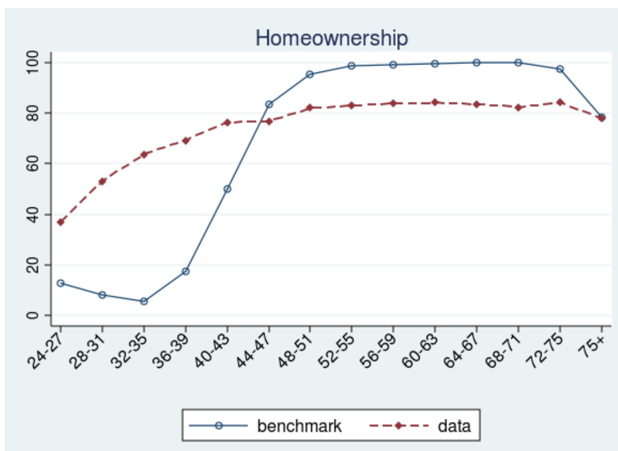
(Data for homeownership, wealth and earnings from the Survey of Consumer Finances, averages from 1989–2004. Data on moving rates and foreclosure from Equifax)



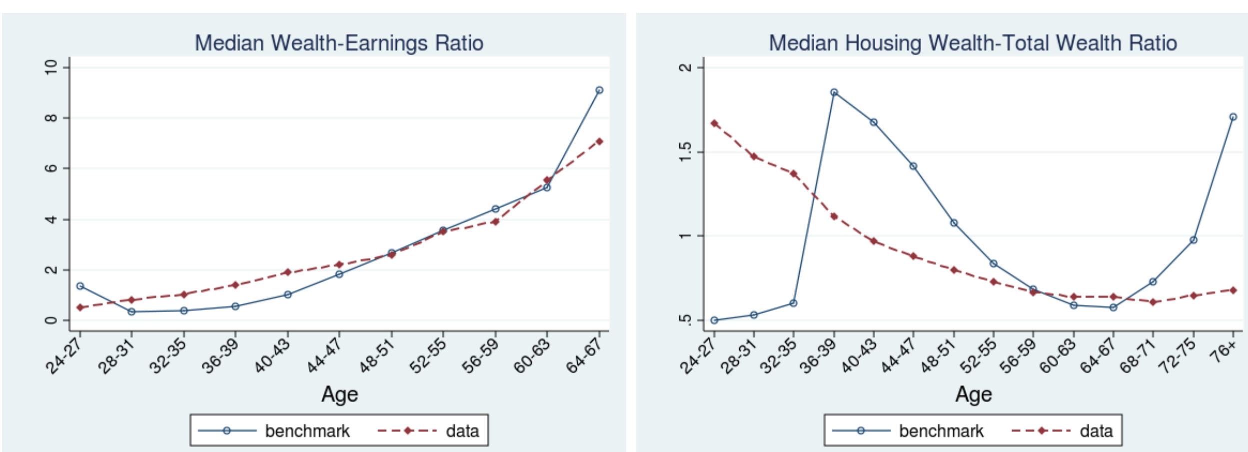
(a) Overall moving rates



(b) Foreclosure rate (out of total households)



(c) Homeownership



(d) Wealth and Earnings

Appendix A. Supplementary results for online Appendix

In this appendix, we display supplementary results. In Table A-1, we show correlations for the raw variables (without removing person-specific averages) for completeness. Some expected patterns, such as a positive correlation between subprime scores and foreclosures are much stronger in this table than in the Table 3 in the text, where individual fixed effects are removed. This reflects the cross-sectional patterns which are neutralized in the latter table—some individuals have permanently low scores and are likely to default.

Table A-2 shows the results of our main specification when individual fixed effects are not included. The patterns for low equity individuals (no lock-in effect) are similar to the results of Table 4 which properly, we argue, includes individual fixed effects. The coefficient for individuals with high positive equity changes sign to negative from positive in Table 4. This means that individuals with permanently high positive equity are less likely to move, maybe reflecting that they are older, while individuals who move from other categories into this equity position are more likely to move.

One could also notice that the coefficients to "Subprime score" and "Near prime score" turn negative, maybe reflecting that more educated individuals are more mobile and also have higher scores. The point of these remarks is not so much that the offered conjectures are likely to be correct but rather that regressions without fixed effects capture cross-sectional patterns, whatever they are, and that such regressions may be misleading for examining non-cross-sectional questions such as the one studied in the present paper; namely, whether housing equity constrains mobility in regions that are hit by labor market shocks.

Table A-3 repeats the main regression of Table 4 with more equity categories. We observe more clearly a U-shaped pattern of migration in equity, but the finding that very low equity is correlated with higher mobility remains robust.

Finally, in Table A-4, we repeat the main regression of Table 4 using actual current equity as reported by CoreLogic in their TrueLTV dataset.[37] Current equity is likely to be endogenous to mobility (why pay on a mortgage, if one has decided to walk away from the house in the near future?). The finding of relatively high mobility for households with very negative equity remains robust.

[37]CoreLogic matched mortgages found in LoanPerformance dataset to subsequent liens taken out on the same property. The resulting total mortgage indebtedness was combined with CoreLogic's Automated Valuation Model (AVM) to estimate "true LTV."

Table A-1: Correlation matrix. CBSA $\times$ Year Fixed Effects removed. Individual Fixed Effects not removed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Moved MSA	1.000									
(2) Neg. shock times eq. ≤–20%	0.0102	1.000								
(3) Pos. shock times eq. ≤–20%	0.0018	0	1.000							
(4) Neg. shock times eq. (–20,0)%	0.01	-0.3184	0	1.000						
(5) Pos. shock times eq. (–20,0)%	0.0053	0	-0.1866	0	1.000					
(6) Neg. shock times eq. [0,20)%	0.0055	-0.1938	0	-0.2987	0	1.000				
(7) Pos. shock times eq. [0,20)%	0.0071	0	-0.1006	0	-0.2904	0	1.000			
(8) Neg. shock times eq. >20%	-0.0201	-0.1912	0	-0.3036	0	-0.6335	0	1.000		
(9) Pos. shock times eq. >20%	-0.011	0	-0.0859	0	-0.263	0	-0.8033	0	1.000	
(10) Foreclosed	0.0457	0.1076	0.0222	0.0633	0.0426	0.0222	0.0386	-0.1422	-0.072	1.000
(11) Mortg. age	-0.0108	-0.1333	-0.0455	-0.1113	-0.1067	-0.1146	-0.1645	0.2896	0.2456	-0.0855
(12) Subprime score	-0.0034	0.0899	0.0296	0.0327	0.0393	0.0068	0.031	-0.0908	-0.0644	0.2394
(13) Near prime score	-0.0047	0.024	0.0108	0.0183	0.0188	0.0205	0.0388	-0.0506	-0.054	0.0146
(14) Log score	0.0045	-0.134	-0.0484	-0.0698	-0.0699	-0.0432	-0.0863	0.1854	0.1448	-0.2713
(15) Equity≤–20%	0.0101	0.9237	0.3832	-0.2941	-0.0715	-0.179	-0.0386	-0.1766	-0.0329	0.1079
(16) Equity (–20,0)%	0.0113	-0.2645	-0.1039	0.8308	0.5565	-0.2482	-0.1616	-0.2523	-0.1464	0.0763
(17) House Price Gr ≤–20%	-0.0009	0.0301	0.0562	0.0219	0.0278	-0.0085	-0.007	-0.0285	-0.0269	0.0109
(18) House Price Gr (–20,0)%	0.0014	-0.0296	-0.0547	-0.0118	-0.0044	0.0145	0.0177	0.014	0.0013	-0.0095
(19) House Price Gr [0,20)%	-0.0004	-0.0001	-0.0007	-0.0091	-0.0235	-0.0086	-0.0162	0.016	0.031	-0.0026
(20) House Price Gr >20%	-0.0003	0	0	-0.0022	-0.002	0.0026	0.0061	-0.0008	-0.0049	0.0016
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(12) Subprime score	-0.0509	1.000								
(13) Near prime score	-0.0547	-0.251	1.000							
(14) Log score	0.1471	-0.7489	-0.1954	1.000						
(15) Equity≤–20%	-0.1406	0.0943	0.0263	-0.1423	1.000					
(16) Equity (–20,0)%	-0.1519	0.049	0.0257	-0.0969	-0.2841	1.000				
(17) House Price Gr ≤–20%	-0.0089	0.0154	0.0055	-0.0246	0.0493	0.0337	1.000			
(18) House Price Gr (–20,0)%	0.0095	-0.0155	-0.0077	0.0283	-0.0483	-0.0123	-0.4738	1.000		
(19) House Price Gr [0,20)%	0.0095	-0.007	-0.0065	0.0173	-0.0004	-0.0207	-0.3876	-0.4027	1.000	
(20) House Price Gr >20%	-0.0143	0.0102	0.0124	-0.03	0	-0.003	-0.2364	-0.2456	-0.2009	1.000

Table A-2: TransUnion, years 2007–2009. Moving CBSA. No Individual Fixed Effects.

Neg. shock × equity $\leq -20\%$	0.67***
	(9.12)
Neg. shock × equity$(-20, 0]\%$	0.43***
	(8.54)
Neg. shock × equity$[0, 20)\%$	excluded group
Neg. shock × equity $\geq 20\%$	–0.56***
	(–16.53)
Pos. shock × equity $\leq -20\%$	0.11
	(0.76)
Pos. shock × equity$(-20, 0]\%$	0.15***
	(2.73)
Pos. shock × equity$[0, 20)\%$	excluded group
Pos. shock × equity $\geq 20\%$	–0.40***
	(–13.32)
Foreclosure dummy	2.90***
	(35.93)
Subprime score	–0.67***
	(–25.21)
Near prime score	–0.50***
	(–18.40)
Mortgage age	0.00
	(0.46)
CBSA × year effects	Y
Individual effects	N
No. obs.	6,581,245
No. clusters	5631
No. indiv.	3,007,744

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment growth in a CBSA and the four equity dummies are variables reflecting the extent of mortgage equity at time $t-1$. See Section 3.2 for a detailed variable description. $\delta_j \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table A-3: TransUnion, years 2007–2009. Moving CBSA. More equity dummies.

Equity $< -50\%$ x Neg. shock	2.21*** (10.70)	Equity $< -50\%$ x Pos. shock	0.98 (1.62)
Equity $[-50, -40)\%$ x Neg. shock	1.47*** (9.33)	Equity $[-50, -40)\%$ x Pos. shock	0.55 (1.27)
Equity $[-40, -30)\%$ x Neg. shock	1.13*** (9.36)	Equity $[-40, -30)\%$ x Pos. shock	0.62** (2.31)
Equity $[-30, -20)\%$ x Neg. shock	0.79*** (8.17)	Equity $[-30, -20)\%$ x Pos. shock	0.74*** (4.52)
Equity $[-20, -10)\%$ x Neg. shock	0.47*** (6.73)	Equity $[-20, -10)\%$ x Pos. shock	0.55*** (5.78)
Equity $[-10, 0)\%$ x Neg. shock	0.31*** (5.79)	Equity $[-10, 0)\%$ x Pos. shock	0.37*** (5.86)
Equity $[0, 10)\%$ x Neg. shock	excluded group	Equity $[0, 10)\%$ x Pos. shock	excluded group
Equity $[10, 20)\%$ x Neg. shock	–0.06 (–1.35)	Equity $[10, 20)\%$ x Pos. shock	0.01 (0.29)
Equity $[20, 30)\%$ x Neg. shock	–0.11*** (–2.08)	Equity $[20, 30)\%$ x Pos. shock	0.01 (0.09)
Equity $[30, 40)\%$ x Neg. shock	0.02 (0.31)	Equity $[30, 40)\%$ x Pos. shock	0.16** (2.02)
Equity $[40, 50)\%$ x Neg. shock	0.07 (0.78)	Equity $[40, 50)\%$ x Pos. shock	0.34*** (3.31)
Equity $\geq 50\%$ x Neg. shock	0.22* (1.76)	Equity $\geq 50\%$ x Pos. shock	0.59*** (4.37)
Foreclosure dummy	1.82*** (26.13)	Mortgage age	0.73*** (11.20)
Subprime score	0.43*** (10.33)	CBSA x year effects Individual effects	Y Y
Near prime score	0.18*** (5.35)	No. obs. No. clusters	6,581,245 5631
		No. Indiv.	3,032,070

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. See Section 3.2 for a detailed variable description. $\delta_j \times \mu_{t-1}$ are (lagged) CBSA $\times$ year fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table A-4: TransUnion, years 2007–2009.
Moving CBSA. TrueLTV equity.

Neg. shock $\times$ equity$\leq -20\%$	0.31**
	(2.40)
Neg. shock $\times$ equity$(-20, 0]\%$	0.04
	(0.49)
Neg. shock $\times$ equity $[0, 20)\%$	excluded group
Neg. shock $\times$ equity$\geq 20\%$	0.24***
	(2.60)
Pos. shock $\times$ equity$\leq -20\%$	0.08
	(0.43)
Pos. shock $\times$ equity$(-20, 0]\%$	0.09
	(0.83)
Pos. shock $\times$ equity $[0, 20)\%$	excluded group
Pos. shock $\times$ equity$\geq 20\%$	0.34***
	(3.28)
Foreclosure dummy	1.43***
	(9.77)
Mortgage age	0.23
	(0.69)
Subprime score	0.26***
	(3.12)
Near prime score	0.11
	(1.50)
CBSA $\times$ year effects	Y
Individual effects	Y
No. obs.	1,588,448
No. clusters	10786
No. indiv.	933,727

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_{t-1} + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment growth in a CBSA and the four equity dummies are variables reflecting the extent of home equity at time $t-1$. See Section 3.2 for a detailed variable description. $\delta_j \times \mu_{t-1}$ are (lagged) CBSA $\times$ year fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.