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

Yuliya Demyanyk†
Federal Reserve Bank of Cleveland

Dmytro Hryshko ‡
University of Alberta

María José Luengo-Prado§
Federal Reserve Bank of Boston

Bent E. Sørensen¶
University of Houston and CEPR

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Abstract

We use individual-level credit reports merged with loan-level mortgage data to estimate how home equity interacted with mobility in relatively weak and strong labor markets in the United States during the Great Recession. We construct a dynamic model of housing, consumption, employment, and relocation, which provides a structural interpretation of our empirical results, and allows us to explore the role that foreclosure played in labor mobility. We find that negative home equity is not a significant barrier to job-related mobility because the benefits of accepting an out-of-area job outweigh the costs of moving. This pattern holds even if homeowners are not able to default on their mortgages.

*The views expressed are those of the authors and do not necessarily reflect the official positions of the Federal Reserve Bank of Boston, the Federal Reserve Bank of Cleveland, or the Federal Reserve System.

†yuliya.demyanyk@clev.frb.org
‡dmytro.hryshko@ualberta.ca
§maria.luengo-prado@bos.frb.org
¶besorensen@uh.edu

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 the mobility of unemployed workers. Mobility suffers if unemployed workers are reluctant to leave homes that, with debt exceeding value (being "underwater"), 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 relationship between vacancies and joblessness, may shift outward.[1] Figure 1 shows the geographical distribution of negative equity in the United States over the years 2006–2009. Negative equity was prevalent in Michigan in 2007 and in a large number of states in 2009.

We study mobility between U.S. metro areas—defined as Core Based Statistical Areas (CBSAs)—using anonymized credit report data from a major credit bureau. Our main finding is that labor market adjustment in the United States was not significantly hampered by households with negative home equity relocating relatively less often than other households. Our very large dataset allows us to control for unobserved heterogeneity using individual fixed effects and for unobserved local housing and labor market conditions using ZIP code fixed effects for each year. We estimate two sets of empirical regressions. First, we use home equity predicted from initial loan-to-value ratios and house price appreciation at the ZIP code level to show that the level of individuals' home equity correlates negatively with mobility. The use of predetermined variables delivers reduced-form estimates which may be useful for predicting the effect of exogenous house-price changes. Second, we regress mobility on a broader set of variables, which are not all exogenous, in order to provide more stylized facts for models to match.

We construct a model of households who choose nondurable consumption and housing services, who can lose their jobs, and who receive job offers, some

[1] For example, the *Economist* of August 28, 2010, tells this story in an article discussing high unemployment in the United States during the Great Recession (page 68, and leader, page 11).

of which are non-local and can only be accepted by relocating.[2] Households will opt to move if the expected lifetime benefit of moving outweighs the costs of buying and selling houses. The model replicates the patterns in the data well and therefore provides a structural interpretation of our empirical findings. In particular, the model allows us to explore the roles of variables which are not present in our dataset; in particular, households' age, income, wealth, and labor market status. Unsurprisingly, the unemployed are more likely to move to another CBSA because their gain from doing so is larger than for the employed. Moreover, unemployed individuals with negative home equity are disproportionately more likely to move, and more strongly so, if the local labor market is weak. High home values are negatively associated with mobility; however, the most important determinants of CBSA mobility are whether the homeowner is employed and/or underwater.

Households often default on their mortgages before moving, so we use our model to explore whether the foreclosure option is important for mobility in recessions by simulating a version of the model with no possibility of mortgage default. We find that even without foreclosure, households are more likely to leave areas with falling house prices although the difference to households in other areas is smaller than in the case with foreclosure. We also find that households maintain more housing equity before moving, compared with households in the model that allows for foreclosure. We further use the model to calculate welfare gains from having workers being able to move across CBSAs.

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

[2]Because our model involves households we refer to the mobility, jobs, etc. as related to "households" for brevity even though we do not observe households in the data.

2 Literature Survey

There is a substantial literature on mobility, housing, and labor market conditions, but only a few studies utilize home equity data. Ferreira, Gyourko, and Tracy (2010)—updated in Ferreira, Gyourko, and Tracy (2011)—study the relationship between mobility and negative equity using the American Housing Survey 1985–2009 and find that homeowners with negative equity 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 movers from the data. The main advantage of our dataset over the American Housing Survey is that we follow individuals and not homes and, therefore, we can control for individual-specific fixed effects. Coulson and Grieco (2013) study the relationship between mobility and 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 during the Great Recession—they do not consider local labor market status nor provide a model. They do not have exogenous measures of equity, although they can control for changes in income and family size; however, their empirical results are consistent with ours. Chan (2001) reports a reduction in household mobility due to falling house prices during 1989–1994 using a sample of mortgages from Chemical Bank that includes equity but lacks geographical information. None of the studies cited have datasets large enough to control for individual-level heterogeneity using fixed effects, and the issue of mobility versus equity is not yet fully settled.

Several papers examine the relationship between mobility and house prices, but the conclusions of these papers are also ambiguous. Donovan and 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.[3] This lock-in effect is almost entirely due to a reduction

[3]The American Community Survey does not publish individual-level data, so only aver-

in within-county mobility, which is unlikely to be associated with moving to a job; therefore, they conclude that housing market lock-in does not cause higher unemployment rates. Engelhardt (2003), using individual-level data from the National Longitudinal Survey of Youth 1985–1996, finds that falling prices do not constrain mobility. Modestino and Dennett (2013) find evidence for housing lock-in using state-level data from the Internal Revenue Service, while Schmitt and Warner (2011) find that displaced workers' frequency of moving to another county or state is independent of house-price depreciation. Hryshko, Luengo-Prado, and Sorensen (2011) document that moving rates are relatively lower for households with low liquid wealth that become displaced, particularly when house prices depreciate, but that study does not include individual fixed effects and does not consider housing equity.

Many papers focus on the modeling of housing and job-related mobility following Oswald (1997), who suggests that homeownership impacts labor-market clearing because high costs of selling and buying houses limit geographical mobility.[4] We outline the content of a few recent papers related to our work: Guler and Taskin (2011) build a model where agents prefer ownership to renting and search for jobs and homes, and where it is costly to sell homes. The model can explain why homeownership correlates with unemployment across regions, although the model includes neither credit constraints nor region-specific house prices. Using CBSA-level vacancy and housing data, they observe that increased homeownership during 1990–2005 correlates with higher unemployment in weak, but not in strong, local labor markets. Head and 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

ages across individuals can be observed.

[4]While Green and Hendershott (2001) confirm Oswald's hypothesis, Munch, Rosholm, and Svarer (2006), using Danish micro-level data, do not find much support for the hypothesis of limited geographical mobility of homeowners. For further results, see Coulson and Fischer (2002) and Coulson and Fisher (2009). A different, quite voluminous, strand of the mobility literature focuses on the income elasticity of geographical mobility: see Gallin (2004), Bayer and Juessen (2012), and Kennan and Walker (2011).

than renters and have higher unemployment, which implies potentially large differences in unemployment between cities, but the effect on aggregate unemployment is minor. Sterk (2015) simulates a Dynamic Stochastic General Equilibrium model with a labor market matching function such that a fraction of job offers can be accepted only if workers move. Workers are homeowners and have to provide down payments, so a decline in house prices forces some workers to reject job offers. The model implies a causal effect of declining house prices on unemployment.

Finally, there is literature on matching, more tangentially related to our work, such as Barnichon and Figura (2011), who use data from the Current Population Survey 1976–2010 to show that the efficiency of the aggregate matching function has fallen steeply since the onset of the Great Recession, and that local (defined as industry/geography cells) labor market conditions play a significant role. Barnichon et al. (2012), 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. Farber (2012), using the Displaced Workers Survey, finds no evidence of housing lock-in by comparing homeowners with renters. None of these authors had direct information on home equity.

Our model is partial equilibrium and focuses on the incentives to move for individuals with high versus low home equity; it is not informative about aggregate mobility or about people's moving destination, but examines the relationship between equity and mobility in much more detail than work done in a general equilibrium setting. Our results are also uninformative about secular trends.[5]

[5] Kaplan and Schulhofer-Wohl (2012) 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 occupational returns.

3 Data, Regression Specification, and Results

3.1 Data

We measure mobility and individual-level home equity using a very large dataset from TransUnion (TU)—one of the three major credit bureaus in the United States—merged with another dataset, the loan-level LoanPerformance Securities Database (LP) provided by CoreLogic. The merging was done by TU. The combined dataset is called Consumer Risk Indicators for Residential Mortgage-Backed Securities, for which we will use the label "TU-LP." We measure mobility for the years 2007–2009, when housing lock-in may have been important because of the Great Recession, but use data for the years 2005–2009 to allow for lagged controls. We know the exact date of loan origination even if it is much earlier.

The LP dataset has information on loan and borrower characteristics for about 90 percent of all non-agency securitized mortgage loans, totalling about 16 million subprime and Alt-A first-lien loans and about 2 million prime first-lien loans. (In the following, we use the terms "mortgage" and "loan" interchangeably for the more cumbersome term "mortgage loan").[6] For each mortgage, we observe the cumulative loan-to-value (LTV) ratio at the time of loan origination defined as the sum of the balances of all the mortgage(s) taken out together divided by the home value (any non-first lien mortgage taken at origination is popularly known as a "piggy-back" loan). We also observe the location of the property (ZIP code), an extensive list of other loan characteristics, but no address or credit information after origination. In the TU data, we observe up-to-date mailing ZIP codes, which allow us to determine whether and where an individual moves.

Using the LTV ratio for all liens at origination, we predict home equity assuming the value of the house varies with the average price level in the ZIP

[6] 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.

code where the property is located. Property ZIP codes allow us to merge individual-level data with ZIP code-level house prices and with employment in the CBSA where people live. Our dataset does not have demographic, income, or non-housing wealth information and it is not representative of the U.S. population. However, subprime borrowers, who are over-represented, are particularly likely to have negative home equity.

In the combined TU-LP dataset, if a person has a mortgage terminated at time t, we do not have information on that individual's homeownership status and home equity at time $t+1$ unless he or she secures another LP loan. We, therefore, do not normally observe multiple moves for the same person. For a clean sample selection, we drop the low number of individuals who remain in the sample after moving. (In order to have the exact same sample selection, we drop households after they move when using simulated data.)

We augment the TU-LP data with characteristics for ZIP codes, CBSAs, and states.[7] We use the U.S. ZIP Code Database to match CBSAs/states and ZIP codes.[8] CBSA-level and state-level unemployment rates and employment levels are obtained from the Bureau of Labor Statistics.[9] 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. Further details about the data and data cleaning are provided in Appendix A. All appendices are available online.

3.2 Regression specifications

In our reduced form regressions, we estimate the likelihood of moving using the linear probability model:

[7]According to the U.S. Census Bureau, 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.

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

[9]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 are also included.

$$M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}, \tag{1}$$

where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. We focus on mobility between CBSAs because workers typically change jobs when moving to another CBSA, whereas ZIP codes are small and workers often move ZIP codes without changing jobs. For robustness, we show the results of a few regressions considering interstate mobility. $D_{zt-1} \times \mu_{t-1}$ denotes (lagged) ZIP code (z) fixed effects interacted with year dummies, which we refer to as "ZIP × year" fixed effects or dummies.[10]

X is a vector of (lagged) variables of interest to be defined precisely in the next subsection. In order to relate to the literature on equity and mobility, we first show results using exogenous equity dummies (interacted with labor market indicators), and we next include other potentially important variables which may be endogenous to mobility. In particular, we include home value and mortgage balance—the inclusion of these variables allows us to examine if the effect of negative equity may capture a direct effect of home values, mortgage balance, or both, and it allows us to examine the fit to the model more closely. Explanatory variables are lagged one year for the analysis to reflect conditions before the decision to move is made.

All ZIP code (and therefore also CBSA and U.S. aggregate) specific features and trends are captured by the ZIP × year dummies. The inclusion of ZIP × year fixed effects implies that the regressors are identified from the individual variation relative to average values across all individuals in the ZIP code where an individual lives in a given year. Also, our results are not driven by constant individual-specific characteristics (for example, high impatience, which may simultaneously result in high mobility and low home equity) because of the inclusion of individual fixed effects. Because of the individual fixed effects, individuals with regressors that do not change over time will not contribute to identification. We include a somewhat heuristic derivation of these points

[10] z is implicitly a function of i.

in Appendix B.

We use a linear probability model because little is gained by adopting non-linear models, such as probit and logit models, in panels with a short time dimension and a large number of individuals. Ferreira, Gyourko, and Tracy (2010) use a probit model, but they do not allow for individual fixed effects. Greene (2004) shows that fixed effects probit and logit models deliver severely biased (and inconsistent) estimates in such panels; besides, the linear probability model is computationally less burdensome which is important when allowing for both individual and ZIP × year fixed effects. The linear probability model is not a maximum-likelihood estimator, but efficiency is not an important concern when the dataset is as large as ours.

3.3 Variable definitions

We examine mobility between years $t-1$ and t. For our first set of regressions, we create a dummy variable, "Neg. shock," which is equal to one if the unemployment rate in the CBSA of residence increased more than the aggregate U.S. unemployment rate at $t-1$, and a dummy variable, "Pos. shock," which equals one if the increase was less than the U.S. average. Following Demyanyk (2014), we define equity for property i at time $t-1$ as:

$$\%\text{Equity}_{i,t-1} = 100\left(1 - \text{LTV}_{i,0} \times \frac{\text{ZIP HPI}_{i,0}}{\text{ZIP HPI}_{i,t-1}}\right)\%, \qquad (2)$$

where $\text{LTV}_{i,0}$ is the cumulative loan-to-value ratio at origination, and we proxy the change in the value of a property since origination by the change in the house-price index at the ZIP code level between the origination period ($\text{ZIP HPI}_{i,0}$) and time $t-1$ ($\text{ZIP HPI}_{i,t-1}$).

We create dummy variables that group homeowners into four categories based on the estimated amount of equity relative to home value: "Equity $\leq -20\%$" equals one if home equity is negative in an amount that exceeds 20 percent of the home value (zero otherwise), while "Equity $(-20, 0)\%$" equals one if home equity is negative, but numerically less than 20 percent. "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, respectively.[11] (In Appendix C, 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, obtaining eight dummy variables.

Our measure of home equity relies on initial equity and variation in local house prices. After loan origination, the value of a house may change because the homeowner upgrades or cuts back on maintenance, but the resulting changes in equity are badly measured because actual appraisals are done only at loan origination. Further, home equity is endogenous to mobility; for example, homeowners who expect to default may stop maintaining their house, while homeowners who plan to sell may be extra diligent in making their house attractive. Mortgage payments may also be withheld by homeowners planning to move, so for our main reduced form regressions, we use "predicted" equity, calculated using exogenous (to the owner) house prices and ignoring repayments. This is reasonable because our sample has a short time dimension and the majority of loans in the sample are recent.

For our second set of empirical regressions, we calculate "Home Value$_{i,t-1}$" as $\log\left(\frac{1}{\text{LTV}_{i,0}} \times \text{Orig. Amount}_{i,0} \times \frac{\text{ZIP HPI}_{i,t-1}}{\text{ZIP HPI}_{i,0}}\right)$, where "Orig. Amount$_{i,0}$" is the mortgage amount at origination. We create a dummy variable "Equity< 0" that is equal to one if a home is underwater in period $t-1$ and zero otherwise, and we calculate the endogenous variable "Mortgage$_{i,t-1}$," defined as the logarithm of the mortgage balance at time $t-1$ from the LP data.

Table 1 summarizes the distribution of the variables used in the regressions. 1.15 percent of the individuals in our sample change CBSA in a given year, 4 percent have negative equity exceeding 20 percent of the home value, while another 12 percent are more moderately underwater. Other notable numbers in Table 1 are that 55 percent of our observations come from regions with negative unemployment shocks, while 44 percent of individuals held subprime mortgages, 21 percent prime mortgages, and 34 percent Alt-A mortgages.

[11] Ferreira, Gyourko, and Tracy (2010) use one dummy for negative equity in their smaller sample.

Table C-1 in Appendix C documents that moving rates declined substantially from 2007 to 2009. This holds for our TU-LP data, for data from a more representative sample from the Equifax credit bureau, and for data from the Current Population Survey (CPS). See Appendix C for more details.

3.4 Results

Table 2 displays our main results with robust standard errors clustered by ZIP code. The interactions "Neg. shock $\times$ equity $[0, 20)\%$" and "Pos. shock $\times$ equity $[0, 20)\%$"—people with low but positive equity, facing a negative or a positive regional shock, respectively—are omitted to avoid perfect multicollinearity.[12] As previously discussed, all regressions include ZIP $\times$ year and individual fixed effects.[13] (We report the correlation matrix with fixed effects removed from each variable in Appendix C). The first eight regressors in Table 2 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.

It is immediately obvious that individuals with very negative equity are not geographically locked in; in fact, they are more likely to move than are individuals with low positive equity. From the first column of Table 2, which considers moves between CBSAs and does not include control variables, we see that compared with the omitted group, individuals with very negative equity positions in CBSAs with negative employment shocks are 1.48 percentage points more likely to leave their area. More precisely, they are more likely to move to another CBSA than individuals with low positive equity in the same ZIP code, during the same year, when their CBSA's unemployment rate

[12] These dummies are not identified if CBSA-year dummies are included, and the ZIP-year dummies subsume these because the CBSA $\times$ year dummies are the sum over the ZIP codes in the CBSA of the ZIP $\times$ year dummies. Time dummies are also subsumed in the ZIP $\times$ year dummies.

[13] In all regressions with individual fixed effects, we deleted "singletons" (individuals who appear in the regression dataset only in one year). Singletons would not affect the results because the fixed effects would fit these observations perfectly, and the degrees of freedom would also be unaffected.

increases relative to U.S. unemployment. A 1.48 percentage points higher moving propensity is significant compared with the average annual CBSA moving propensity of 1.15 percent. In contrast, individuals with high positive equity are 0.16 percentage points less likely to move. In CBSAs with positive employment shocks, the pattern is somewhat weaker: individuals with very negative equity are 1.07 percentage points more likely to leave their CBSAs, while those with high positive equity have moving propensities similar to those with low positive equity (the point estimate for the high group is small at 0.07).

A change in home equity may affect mobility through various channels besides the equity position (for example, wealth shocks may change the consumer's aversion to risk, inclusive of the risk related to relocation) and, in the second column of Table 2, we examine whether the results are robust to the inclusion of the lagged change in equity.[14] An increase in the lagged change in equity, conditional on the equity categories, lowers mobility. The equity shock is highly correlated with the equity categories (correlations are reported in Appendix C), so its inclusion lowers the estimated coefficients of the categories, but the result that individuals with negative equity tend to move relatively more often is robust.[15]

The patterns are qualitatively similar for interstate moves, see column (3), although the estimated coefficients for all variables are lower for these moves (for example, 0.79 for very negative equity in weak labor markets). This result is intuitively reasonable because interstate moving rates are lower in general, involve longer distances, and are more costly.

Even though non-agency securitized mortgages are typically subprime, Alt-A, or jumbo prime (loans that 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

[14] In this column, the number of observations drops by over two million because the lagged change in equity relies on data going back to 2005 where some of the loans are missing because they are not yet originated.

[15] In a previous version, we included a measure of mortgage default, but it did not change the results. We believe this is due to the exact time of default not being precisely identified in the data.

conformed to the agency criteria. We examine the sample of prime non-jumbo mortgages in order to verify that our results are not limited to subprime loans. This is important because prime non-jumbo mortgages are the most common mortgages and also because our calibrations of, for example, life-cycle patterns of homeownership, are based on representative samples of Americans, and not calibrated to subprime borrowers.[16] We report results from this sample in column (4) and observe that the "no lock-in" result carries over to prime borrowers with very negative equity. Individuals with very negative equity are 1.74 percentage points (1.68 percentage points) more likely to move out of CBSAs with negative (positive) labor market shocks than individuals with low positive home equity. These coefficients are larger than those found for the full, mainly subprime, sample, implying that our results are not specific to subprime movers.

In Appendix C, we display a number of empirical tables which demonstrate that our findings regarding equity and labor markets are robust to using different types of mortgages (jumbo, Alt-A, subprime, investment properties), and to whether labor market shocks are measured using employment growth or vacancy rates. The results are similar if we focus only on states that do not give lenders recourse to go after a borrower's assets in addition to the mortgaged house.[17]

The results are also supportive of our conclusions if we allow for more equity categories or more labor market categories. The results are further robust to the inclusion of credit scores, and to the use of CBSA $\times$ year fixed effects rather than ZIP $\times$ year fixed effects. Dropping individual fixed effects does not change the conclusion regarding negative equity, even though the coefficients to the credit scores change drastically.

Overall, the relationship between home equity and mobility is robustly

[16] Prime non-jumbo mortgages constitute a small fraction of our dataset, but there are still more than 648,440 observations in this subsample (after deleting singletons).

[17] Anecdotal evidence suggests that lenders were too overwhelmed with foreclosures to pursue the assets of defaulting borrowers in the Great Recession. In other periods, recourse states have been different: Ghent and Kudlyak (2011) find higher tendencies to default in non-recourse states for the period 1997–2008.

estimated across different types of borrowers, across different types of states, and across different specifications. In view of this finding, and considering the very large number of observations used, we conclude that lock-in did not adversely affect regional labor market adjustment during the Great Recession. Rather, the benefits of relocating for a job, when possible, outweighed the costs of disposing of underwater mortgages.

In Table 3, we broaden the focus from the impact of equity on mobility and include (lagged) home values and mortgages.[18] The regressors in this table are not exogenous—for example, the lagged mortgage balance may be endogenous to the moving decision if households stop paying on the mortgage because they expect to default and move—and the table serves to provide statistics to be compared with those from the model. The interpretation of the results will be provided from the model simulations, where it is possible to include variables that are unobserved in the data. We drop the ZIP $\times$ year fixed effects in order to get more precise estimates of the effect of home values for which there is a lot of variation at the ZIP code level.[19] We include individual fixed effects, which retains the interpretation of the regressions as capturing the effects of the changes in the variables over the three-year span, rather than the effects of the levels (and also absorbs ZIP code constant effects), and we include year fixed effects. In order to present a less cluttered table, we only include one dummy for negative equity. In this table, one dummy for labor market shocks is identified and, not surprisingly, individuals are more likely to leave regions with negative labor market shocks.

In the first column of Table 3, the (logarithm) of the home value interacted with the dummy for weak or strong labor markets is included. Homeowners with 10 percent higher property values are about 0.162 (0.148) percentage points less likely to move in weak (strong) labor markets, consistent with positive equity discouraging mobility. The second column adds mortgage balances.

[18]We also explored regressions including the house price index, but the results were unstable because the index is highly correlated with predicted home value when household fixed effects are included; the results are not reported for brevity.

[19]Results for this specification with ZIP $\times$ year fixed effects are reported in Appendix Table C-7.

The coefficient to the home value does not change much and higher mortgage balances predict mobility positively, and more so in weak labor markets. The coefficients imply that a mortgage balance which is 10 percent higher is associated with 0.158 (0.116) percentage points higher mobility in weak (strong) labor markets. The third column further includes the equity dummy. Households that are underwater are more likely to move with very high statistical significance—the estimated effect is similar to the effect of low negative equity in Table 2. Including the negative equity dummy makes the coefficients to home value and mortgage balance numerically smaller than in the previous columns indicating that their effects partly work through the equity position. The coefficient to negative labor market shocks is much smaller in columns (2) and (3), suggesting that a lot of the mobility out of depressed regions is associated with individuals not paying down their mortgage and having negative equity. The results in Table 3 cannot be directly compared to those of Table 2 because the mortgage balance is endogenous, but, clearly, mobility depends on whether the household is underwater or not. We next turn to formulating the model.

4 The Model

We construct a model of forward-looking consumers who may lose their jobs, who choose whether or not to become homeowners, and who face reasonable costs of buying and selling real estate. We calibrate and simulate the model and perform regressions on simulated data. We verify that the results using model data match the results using empirical data, and we then use the model to provide a structural interpretation of our results and to perform counterfactual analysis. In particular, we analyze the role of mortgage default.

The model builds on Díaz and 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, and consumers can move in order to free up equity or to increase housing consumption, (2) individuals may be employed or unemployed, (3) unemployment duration can be shortened by moving to another location, (4) employed individuals may improve their earnings potential by moving, (5) moving is costly, particularly for homeowners, (6) mortgage default is permitted. Briefly, individuals in the model have finite life-spans and derive utility from consuming nondurable goods and housing services that can be obtained in the rental market or through homeownership. House buyers pay a down payment, buyers and sellers pay transactions costs and housing equity above a required down payment can be used as collateral for loans. There are no other forms of credit, tax treatment of owner-occupied housing is preferential as in the United States, and individuals face uninsurable earnings risk and uncertainty arising from house-price variation. Individuals can default on mortgages: if an individual defaults, the lender forecloses and "default" and "foreclosure" refer to the same event. Jeske, Krueger, and Mitman (2013) and Mitman (2016) develop similar models with heterogenous agents who choose consumption and housing subject to credit constraints. Their models are embedded in general equilibrium frameworks, but they do not study mobility.[20]

Preferences and demography. Consumers 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 and newborns receive only liquid assets.

Utility is derived from consuming nondurable goods and housing services obtained from either renting housing services in the amount S, or owning a home of size H (it is not possible to rent and own a home simultaneously). One unit of housing stock provides one unit of housing services. The per-period utility at age t is $U\left(C_t, J_t\right)$, where C is nondurable consumption and housing services are $J = o \times H + (1 - o) \times S$, where o is an ownership indicator. The expected lifetime utility in period 0 is $E_0 \sum_{t=0}^{T} (1 + \rho)^{-t} \left[\zeta_t U\left(C_t, J_t\right) + (1 - \zeta_t) B(X_t)\right]$, where $\rho \geq 0$ is the time discount rate, ζ_t is the probability of being

[20] Jeske, Krueger, and Mitman (2013) examine the effects of the implicit federal guarantees to government sponsored agencies (Fannie May and Freddie Mac) on the macroeconomy, while Mitman (2016) studies the implications of bankruptcy and foreclosure legislation for consumer bankruptcy and default rates.

alive at age t, X_t is a bequest, and $B(X_t)$ is the utility of leaving the bequest.

Market arrangements. Consumers start 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 $r_{s,t}$.

A down payment $\theta q_t H_t$ is required to buy a house, so 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 with a maximum LTV ratio of $(1-\theta)$. If house prices go down, a homeowner can 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 $M_t \leq M_{t-1}$. This mortgage specification allows us to consider both down payment requirements and home equity loans without the need to model specific mortgage contracts or mortgage choice, and it can be thought of as a flexible mortgage contract with non-costly principal prepayment and home equity extraction.

A fraction κ of the home value is paid when buying a house (interpreted as, for example, tax or search costs). When selling a house, a homeowner loses a fraction χ of the home value (interpreted as, for example, fees to a real estate agent). The selling cost is slightly increasing in age to better match homeownership profiles. Houses depreciate at the rate δ_h, and homeowners can choose the extent 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. 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. Second, selling the house is the only way to realize capital gains beyond the maximum LTV ratio 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. To match overall moving rates in the United States, we assume there is an exogenous (non-job-related) probability of moving each period.

A homeowner can default subject to the following penalties: loss of any positive equity, paying a percentage ρ_W of current income, and paying small percentages ρ_H and ρ_A of his/her home value and deposits, respectively, at foreclosure. The losses associated with foreclosure (in terms of assets) are included to produce a life-cycle profile of foreclosure that first increases with age and then decreases.[21] After foreclosure, the agent is forced to rent for one period. There is no additional penalty after that, and the consumer can take a job offer in another location (if received) right away. Homeowners are not allowed to default in the last possible period of life. Lenders have no recourse and cannot pursue unpaid mortgage debt after foreclosure.

Earnings and pensions. Working-age individuals can be employed or unemployed and are subject to idiosyncratic risk in labor earnings. For working-age households, labor earnings, W_t, are the product of permanent income, P_t, and two transitory shocks (ν_t and ϕ_t): $W_t = P_t \nu_t \phi_t$. 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—that is, unemployment reduces current income by a certain proportion. Permanent income is $P_t = P_{t-1}\gamma_t \epsilon_t \varsigma_t$. This implies 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 (negative) for currently employed (unemployed) individuals 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 become unemployed each period, while a fraction a_2 of employed workers receive a job offer elsewhere that they may or may not accept (because it

[21]In the model, foreclosure is simultaneous with the homeowner's default.

requires selling their current home if they are homeowners). Employed workers who decline offers remain employed as do the remaining proportion $1-a_1-a_2$. For unemployed workers, a fraction b_1 receive a job offer at their current location and become employed, a fraction b_2 receive a job offer elsewhere and will be employed only if choosing to move, while a fraction $1-b_1-b_2$ receive no job offers and remain unemployed.

Unemployment spells may have a duration longer than one period, either because an unemployed household receives no job offers or because an offer in another labor market was not accepted. Because our objective is not to study where people move, we do not model geographical locations explicitly and 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.[22] 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, $W_t = bP_R$, $\forall t > R$.[23]

House-price uncertainty. House prices are uncertain and assumed to follow a highly persistent AR(1) process. Because we do not follow individuals after they move, we assume they ignore price differentials across locations when deciding whether to move (that is, they assume prices in other locations are similar to local prices).[24] Our specification assumes 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.

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 de-

[22]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.

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

[24]Amior and Halket (2014) consider a model that allows for house-price levels to vary across cities, but they do not study mobility.

ductible with a deduction percentage τ_m. Taxable income in period t is then $Y_t^\tau = W_t + r_a A_{t-1} - \tau_m \, r_m \, M_{t-1}$. Proceeds from taxation finance government expenditures that do not affect consumers 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).[25] To match the targets, we use a discount rate of 3.75 percent, a weight of housing in a Cobb-Douglas utility function of 0.12, and a minimum house size at purchase of 1.6 times permanent income. The general strategy in choosing the 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 (for example, homeownership profiles and foreclosure rates).

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 ($t = 61$). They start life without a job and retire at age 65 ($t = 41$). Survival probabilities are taken from the U.S. Vital Statistics 2003 (for females), published by the National Center for Health Statistics.[26] 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

[25] We use the average of six years of SCF data: 1989, 1992, 1995, 1998, 2001, and 2004.

[26] Because the agents in our model represent households, we use numbers for females because they tend to live longer.

wealth, X_t, is

$$B(X_t) = \frac{\left(X_t \alpha^{\alpha}[(1-\alpha)/r_{s,t}]^{1-\alpha}\right)^{1-\sigma}}{1-\sigma},$$

where $r_{s,t}$ 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 net financial assets: $X_t = q_t H_t(1-\delta_h)(1-\chi) + A_t - M_t$. Households receive only financial assets at birth and start life as renters. With Cobb-Douglas utility, inheritors will choose fixed expenditure shares on non-durable consumption and housing services, α and $(1-\alpha)$, which explains the specification for $B(X_t)$.

We follow Cocco, Gomes, and Maenhout (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 median household (0.01 and 0.073, respectively).[27] These values are typical in the literature (see Storesletten, Telmer, and 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, Gomes, and Maenhout (2005). The unemployment replacement rate is 60 percent.

We let groups of individuals live in different labor markets with different house-price shocks, and we refer to each group as "a region." In our benchmark case, which we refer to as strong labor markets, an employed worker remains employed in the same location with 90 percent probability, becomes unemployed with 5 percent probability, and receives a job offer from another location with 5 percent probability. The worker has to pay the cost of relocating in order to accept an out-of-region job and may decline the offer but remains employed in this case. An unemployed worker receives no job offers with 5 percent probability, becomes employed in the current location with

[27]Cocco, Gomes, and Maenhout (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 the unemployment shock is equal to their estimate, 0.073.

85.5 percent probability, and receives a job offer from another location with 9.5 percent probability (that is, job offers are 90 percent local and 10 percent non-local). These probabilities produce an average unemployment rate of roughly 5 percent. A job offer in a different location is associated with a one percent increase in permanent income ($\log \varsigma$) for an employed worker and a one percent decline for an unemployed individual. In Appendix D, we consider the sensitivity of our results to alternative calibrations of the wage increases and declines associated with non-local job offers as well as different probabilities of the shocks. We do not keep track of actual locations in our stylized model, but we 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 consider regions that we refer to as weak labor markets, which differ from strong labor markets only in the proportion of local to non-local job offers for the unemployed. We set the probability of no offer for the 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 (that is, job offers are 80 percent local and 20 percent non-local).[28]

Retirees receive a pension of 50 percent of permanent income in the last period of working life. Munnell and 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, Gomes, and Maenhout (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. Consumers can adjust housing consumption by a fraction of up to $\xi = 0.06$ without paying moving costs. 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 in-

[28]When simulating weak labor market regions, we keep parameters other than the proportion of local to non-local offers the same as in the benchmark case.

creases with age from a minimum of 3 percent to a maximum of 6 percent. In particular, $\chi(\text{age}) = 0.01 + 0.02 \times [1 + (\text{age} - 24)]^{0.295}$, which is a short-cut capturing the declining mobility rates observed in the data, which may be due to psychological attachment, children's school, and so on. In order to reduce computational complexity, we do not model such issues, which we expect would provide little gain for our purpose. The overall moving rate for homeowners in our baseline calibration is roughly 8 percent per year, a bit above the 7 percent figure in TU-LP for 2007–2009. The non-local moving rate for owners is 1 percent, in line with TU-LP numbers for interstate moves. The interest rate on deposits, r_a, is 4 percent (the average real rate for 1967–2005, as calculated in Díaz and Luengo-Prado, 2010), while the interest rate on mortgages is 4.5 percent. Foreclosure entails a one-period loss of a fraction, ρ_W, of current income, calibrated to 15.5 percent, plus an additional loss of a fraction, ρ_H, of the current value of the home, calibrated to 2.5 percent, and a fraction, ρ_A, of current financial assets, also calibrated to 2.5 percent.[29] This combination results in a foreclosure rate (defined as the number of homeowners defaulting in a period over the total number of households) of 0.7 percent annually, on par with the number of foreclosures in TU-LP, and a life-cycle profile similar to that in the Equifax data, with foreclosures first increasing with age, peaking at age 39, and then slowly declining.

There is no age limit on credit availability; a homeowner may die with negative equity, but negative bequests are not passed along. 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.[30] 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

[29]The latter costs diminish the incentives to buy a very large house and default.

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

ratio of marginal income tax rates to average tax rates, based on TAXSIM (for details, see Feenberg and 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, rental prices, and depreciation. House prices are modeled as a persistent autoregressive process of order 1, AR(1).

$$q_t = \rho_q q_{t-1} + \varrho_t. \tag{4}$$

The AR(1) process is approximated by a discrete Markov chain with three states, using the Rouwenhorst method, with $\rho_q = 0.9$ and $\varrho \sim$ i.i.d. $N(0, \sigma_\varrho)$, $\sigma_\varrho = 0.091$.[31] To add enough variation in house prices to match the crash while keeping computational time in check, we use three house-price states (low, normal, and high), but allow the number of possible house prices to be higher than the number of states. In particular, when house prices are high, half of the households receive a house-price shock that is 5 percent higher than the value given by our three-point approximation, and the other half receive a house-price shock that is 5 percent lower, and similarly when house prices are low. In summary, house prices can take one of the five values $q^* = \{0.8317,\ 0.9193,\ 1,\ 1.0683,\ 1.1807\}$, and the state variable can take the values $q = \{0.8755, 1.0, 1.1245\}$. The transition matrix for house-price states is:

$$P_{q,q'} = \begin{bmatrix} 0.9025 & 0.0950 & 0.0025 \\ 0.0475 & 0.9050 & 0.0475 \\ 0.0025 & 0.0950 & 0.9025 \end{bmatrix}.$$

The price decline from the high to the low house-price state is roughly 22 percent, in line with the national decline in house prices from 2006 to 2009. The largest possible decline given the additional variation introduced is approximately 30 percent.

[31] We fit an AR(1) process to real house-price indices at the national and at the state level, and we use an average of the estimates.

The housing depreciation/maintenance cost rate for owners, δ_h, is 1.5 percent, as estimated in Harding, Rosenthal, and Sirmans (2007). The depreciation rate for rental units , $\delta_h + \varepsilon$, is 2.5 percent.

The rental price is proportional to the house-price state. In particular,

$$r_{s,t} = q_t \, \frac{(1-\tau_y)r_a + \delta_h + \varepsilon}{(1-\tau_y)(1+(1-\tau_y)r_a)} \ . \tag{5}$$

This can be interpreted as the user cost for a landlord who is neither liquidity constrained nor subject to adjustment costs, and who pays income taxes on rental income. The calibration is consistent with the estimates in Sinai and Souleles (2005), who find the house-price-to-rent ratio capitalizes expected future rents (for more details see Díaz and Luengo-Prado, 2010). For our benchmark calibration, $r_{s,t}/q_t$ is roughly 6.9 percent annually. We list all benchmark calibration parameters in Table 4. Appendix E presents the household problem in recursive form and provides details about the computational procedure.

4.2 Patterns of homeownership and wealth

Figure 2 depicts the evolution of some key variables throughout the life cycle for our baseline calibration. All series are normalized by the mean earnings of all working individuals. Panel (a) shows mean labor income (earnings for workers and pensions for retirees) across workers of a given age and nondurable consumption. For working-age households, the life-cycle profile for earnings is calibrated to the profile estimated by Cocco, Gomes, and Maenhout (2005) for households with a high school degree. Earnings peak at age 47, while consumption peaks 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 age 60–63, with a value of about 3.8 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. Gross housing wealth increases until age 51, then stays fairly constant until it begins to decrease at age 64, when the homeownership rate starts to decline.

In the model, households are impatient but prudent and have an incentive to pay down their mortgages due to the spread between the rates for mortgages and deposits, even with the tax deductability of mortgage interest payments. However, households also have incentives to keep some financial assets at hand because home equity is risky and borrowing becomes infeasible if home equity slips below 5 percent. In our baseline simulations, about 50 percent of households hold deposits of less than 25 percent of their annual permanent income, and about 30 percent hold deposits in excess of their permanent income.

The life-cycle profile of moving rates for homeowners is depicted in panel (c) of Figure 2 (the model does not identify whether renters are moving within the area).[32] The average moving rate for homeowners is roughly 8 percent, and it declines with age. The overall pattern is similar to that in the Equifax data (we cannot use TU-LP because age information is not available to us), with a slight overestimation (underestimation) of moving rates for younger (older) workers. Overall, moving rates decrease with age, a pattern that is not surprising because, conditional on receiving a non-local job offer, the total expected life-cycle gain from higher salaries or escaping unemployment is lower for older individuals.

Panel (d) of Figure 2 depicts homeownership rates by age, which we match fairly well by allowing for age-dependent selling costs. Panel (e) shows the life-cycle pattern of the median wealth-to-earnings ratio for working-age households, while panel (f) depicts the median ratio of home value to total wealth for homeowners over the life cycle. The medians of the wealth-to-earnings and home value-to-total wealth were targets for our calibration—not the life-cycle profiles. Nonetheless, the life-cycle profile of the wealth-to-earnings ratio in the model follows that in the data quite closely, while the median ratio of housing wealth to total wealth is higher in the model than in the data for the youngest cohorts and marginally lower for the oldest cohorts.

[32] Renters do not face any costs of adjusting their consumption of housing services, and they will therefore do so continually. This can be interpreted as if they move every period; however, the model is not intended to be informative about the mobility of renters.

Panel (g) of Figure 2 shows the life-cycle profile of home equity in the data and in the model. The data has a flatter profile than the model. This is likely a result of the model having a limited number of assets; in particular, agents in the model do not have the option of accumulating savings in a tax-protected pension plan, and therefore they are more likely to pay off the mortgage than individuals who have access to such plans.

4.3 The moving decision in the model

We simulate 54 locations (regions hereafter), of which half have (permanently) weak labor markets and half have strong labor markets, each with a population of 40,000, for a number of periods—recall that weak and strong regions differ in the proportion of local versus non-local job offers households receive.[33] House-price shocks are common to all individuals in a given region, while income and employment shocks are idiosyncratic. To mimic the Great Recession, we simulate a period of high house prices followed by a crash. In particular, we allow regions to have their own price dynamics until the last four periods of the simulation, corresponding to the four periods in the data. The sequence of house-price states in the last four periods of the simulation is {3,3,1,1}, with 3 being the highest house-price state and 1 being the lowest. We use data from the last four periods of the simulations in the tables that follow, but the results are similar if more periods are included (we use four years of data in the TU-LP regressions). We compute predicted equity in the simulated data, following the same procedure used with the TU-LP data. We also report results for actual equity, calculated as the difference between the simulated home value and the simulated mortgage balance, which have a different interpretation. Regressions with predicted variables on the right-hand side are useful for predicting the effect of exogenous changes caused by, for example, government policy, while regressions with actual equity are informative about how individuals adjust; for example, individuals who plan to move adjust their equity positions based on whether they plan to default on their mortgage or pay it off.

[33] Regions in the model correspond to ZIP codes in the data, because house prices vary within these units. Weak and strong labor markets correspond to CBSAs in the data.

Model-Based Regressions. In order to match the empirical data, we restrict the sample to homeowners with positive mortgage balances (before the decision on moving is made) and drop households from the sample after their first move, as we did for the empirical regression sample. Further, we randomly drop a number of households with equity above 20 percent until we match the proportion of negative equity observed in the TU-LP data, roughly 15 percent. This adjustment is due to the empirical dataset's focus on subprime movers, and although there is no such thing as a credit score in the model, we will sometimes refer to this as the simulated "subprime" sample for brevity. Finally, we limit our regression samples to homeowners aged 25–60 years.

Columns (1) and (2) in Table 5 show the results from estimating regressions using the simulated data arranged to match the empirical regressions of Table 2 most closely; that is, using the simulated data arranged by region "type" (locally weak or locally strong labor market) without relying on individual-level employment status. As in the empirical analysis, all regressions control for individual and region $\times$ year fixed effects. The results obtained using the simulated data are very similar to the results obtained using the empirical data, see columns (1)–(2). From column (1), for individuals with strongly negative equity, the propensity to move is 1.35 percentage points higher (than for the comparison group) in weak labor markets and 1.04 percentage points higher in strong labor markets. Compare these results with the coefficients of 1.48 and 1.07, in weak and strong labor markets, respectively, from the empirical Table 2. The fit is also quite close for the other categories (small negative coefficients for very positive equity in weak labor markets, for example). In column (2), the change in home equity is added and this variable has a coefficient of –2.52 (compared to –1.63 in the data), implying that a loss of home equity results in higher out-of-region mobility. The coefficient of strongly negative equity drops to 0.80 and 0.49 in weak and strong labor markets, respectively, compared with 1.39 and 1.21 in the data. This decline happens because the change in equity captures some of the variation in equity levels, but the equity dummies remain strongly significant.

In columns (3) and (4), we consider actual equity, although we do not have a good measure of this in the data. Actual equity is endogenous; for instance, agents who plan to default may choose to run down equity. Nonetheless, studying actual equity helps to understand how the model works. 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. From column (4), we observe that wealth shocks are not significant when actual equity is used—likely because the running down of actual equity is such a strong predictor that the household intends to default and move that no further explanatory power is left for the wealth shock. The difference in the results for predicted versus actual equity clearly illustrates that results estimated using actual (lagged) values for equity may not be interpreted as measuring the impact of exogenous changes in equity.

In Table 6, we examine the role of the state variables that can be compared to the data. In these regressions, year and individual fixed effects are included but not region × year fixed effects, and only one equity category is included, as in the corresponding empirical Table 3.[34] The first three columns use actual home value and actual equity, and reflect the endogenous adjustments households make. The first column includes only the home value, but the coefficient hardly changes with the inclusion of the mortgage balance in column (2). The coefficient to actual home value in column (2) is –3.98 (–1.41) and the coefficient to the lagged mortgage balance is 0.14 (0.03), in weak (strong) labor markets. When the equity dummy is included, it captures most of the effect of the changes in home value and mortgage balance as the coefficients to these variables lose most of their explanatory power.

In column (4), we use variables constructed as in the empirical data (predicted home value, lagged mortgage balance, and predicted home equity). The coefficients to these variables were not targeted in the calibration of the model, but in weak labor markets, they have signs consistent with those from the empirical data. The lagged home value has a negative coefficient similar to that of the empirical data, but the coefficient to the mortgage balance is noticeably smaller in numerical terms likely reflecting that the mortgage balance has

[34] Appendix Table D-4 shows the results with region × year fixed effects.

more variation in the model whose households cannot borrow from any other sources. The estimated coefficient to the negative equity dummy is positive, as in the data, although somewhat larger. In strong labor markets, the match is not quite as good, with most coefficients from the model being insignificant. However, the coefficient to the negative equity dummy remains significant and it is similar to the data estimate, with a coefficient of 0.88 in the model versus 0.46 in the data.

The much larger coefficients for endogenous equity are consistent with many households planning to move to a different CBSA and running down their home equity before moving. When the cost of disposing of the house has been eliminated via foreclosure, the benefit of moving to another CBSA if a job offer is received will often dominate the remaining cost involved in doing so.

In Table 7, we study the effect on CBSA mobility of a number of model variables without observed counterparts in the data. We show results both using predicted and actual equity and, for the regressions using actual home values, we introduce state variables gradually in order to evaluate their partial effects. Column (1) repeats the third column of Table 6, and we then add state variables from the model successively in order to evaluate if the effect of the observed variables may be due to omitted variable bias from the forced (in the data) omission of these variables. From column (2), it appears that deposits predict mobility in weak labor markets while permanent income is not significant in any specification. From column (3), employment status is, not surprisingly, a very important determinant of mobility with an unemployed household located in a weak labor market being 11.65 percentage points more likely to move, and 4.74 percentage points more likely to move if living in a strong labor market. Clearly, a worker who receives an out-of-area job offer has a stronger incentive to accept the offer if he or she is unemployed, and this is particularly true in weak labor markets.

We next include a dummy for simultaneously being unemployed and having negative equity. In this column, the coefficient to non-interacted unemployment captures the effect of unemployment for individuals who have positive equity, and the coefficient to the non-interacted equity dummy now captures the effect of being employed and having negative equity. The effect of negative equity on an unemployed individual is the sum of the coefficients to the negative equity dummy and the interaction term. An individual who is both unemployed and has negative equity is a further 6.41 (3.17) percentage points more likely to move CBSA in a weak (strong) labor market than a person who is either unemployed and has positive equity, or a person who is employed and has negative equity. The effect of unemployment is similar to that of the previous column, indicating that unemployed individuals have a strong motive to accept out-of-area job offers even if they have positive equity. The coefficient to negative equity becomes smaller, although it remains significant, which indicates that the effect of negative equity on mobility is, to a large extent, driven by the unemployed. However, the effect of negative equity remains positive in both weak and strong labor markets, implying that employed individuals with negative equity also move more than they would if they had positive equity.

Considering predicted home value and equity in columns (6) and (7), the home value remains significant in weak labor markets, implying that exogenous increases in house prices are important, even if controlling for other effects. Endogenous deposits are positive and significant while exogenous equity for the employed has a modest significant effect. The effects of unemployment and unemployment interacted with the dummy for negative equity are similar to the estimates for actual equity.

Columns (5) and (8) include foreclosures taking place between periods $t-1$ and t. This variable is contemporaneous with the year of potential moves and it is included in order to evaluate if mobility is associated with foreclosure. The coefficient to this variable is systematically large (5–6 percentage points higher mobility when there is foreclosure) and very significant. If a variable loses explanatory power, this indicates that it is correlated with foreclosure. It is striking that the coefficient to equity for employed workers changes sign to become negative, indicating that employed workers who move often do so following a foreclosure. The significance of unemployment (interacted with equity or not) does not change much, implying that foreclosure is not the most important determinant of mobility for the unemployed.

Younger individuals are likely to be more mobile than older individuals and, in Table 8, we explore differences in mobility patterns between "young" and "old" (agents aged 25–45 years and 46–60 years, respectively). There are interesting differences. The mortgage balance is insignificant for the old, and significant for the young in weak or strong labor markets, regardless of whether predicted or endogenous equity and home value are used. Employment status is the most important determinant of CBSA-mobility for young and old, but while negative equity further predicts mobility of the young unemployed (as witnessed by the coefficient to the negative equity dummy interacted with unemployment), negative equity for the unemployed old is only significant in the endogenous variant. In this table, the exogenous negative equity dummy is mainly insignificant, while the endogenous negative equity dummy significantly predicts mobility; especially for the old. Our interpretation is that for the old with negative equity (due to falling home values), the up-front cost of moving tends to outweigh the benefits of accepting a job offer if they are already employed—but if agents plan to move, they let equity go negative and this pattern for the employed is stronger for older workers. Overall, negative equity and unemployment remain the most important predictors of mobility for both age groups.

In Table 9, we explore the role of foreclosure through simulations of a model where the foreclosure option has counterfactually been shut down.[35] Looking first at actual equity in weak regions, the qualitative patterns are fairly similar to those of Table 7 except that negative equity loses most of its predictive power. Comparing these tables, we infer that an employed individual with negative equity defaults on the mortgage if possible, and after foreclosure, the trade-off between staying and accepting an offer from another location tips towards acceptance. For unemployed workers in weak labor markets, the results are fairly similar with or without the default option—this means that the acceptance of an out-of-town job offer is more valuable for an unemployed in-

[35] We set the parameters for the cost of foreclosure so high that no-one will ever choose to default on the mortgage.

dividual with low wealth and this result holds independently of the foreclosure option. In columns (3) and (4), we study the correlations between mobility and predicted equity and home values. Many coefficients are unchanged from columns (6) and (7) of Table 7, but the employed (compare to column (7) of Table 7) no longer move more if equity is negative, while the effect of equity is similar for the unemployed. Again, this finding is consistent with employed individuals no longer being able to gain from a combined foreclosure/moving decision, while unemployed individuals with little equity move to a job if they can.

Welfare Analysis. Finally, we briefly evaluate the partial-equilibrium welfare gains implied by having the ability to move to other regions, across all individuals, over the four-year recession period modeled. We find that disallowing moves to other regions is equivalent to a permanent reduction in nondurable consumption of about 2 percent. An alternative, possibly more realistic, experiment is to evaluate the utility gain for workers of a subsidy that pays half of all moving costs. Such a subsidy would increase welfare, and is equivalent to a permanent increase of nondurable consumption of roughly 0.5 percent; see Appendix F for more information. We do not consider employer benefits of matching, crowding out of other workers, and a host of other potentially important issues, which implies that the potential welfare gains are only suggestive. We leave it for future work in general equilibrium frameworks to evaluate the overall benefits of geographical labor mobility. However, our simple calculations suggest that such gains are not negligible.

5 Conclusion

Using a large sample of credit report data matched with mortgage loan-level data, we find that individuals with negative home equity are more likely than other residents in their ZIP code to move to another labor market. We construct a model of households who choose nondurable consumption and housing services, who can lose their jobs, and who receive job offers, some of which are not local and can only be accepted by relocating. The patterns in the data are replicated well by the model which therefore provides a structural interpretation of our empirical findings. Using the model, we explore the role of variables that are not in our dataset; in particular, households' age, income, wealth, and labor market status. We find that the most important determinants of CBSA mobility are whether the homeowner is employed and/or underwater. If homeowners are not allowed to default on their mortgages, the correlation between negative equity and mobility is weaker for employed individuals. However, unemployed individuals with low equity are still relatively more mobile.

In summary, reduced-form regressions and quantitative modeling demonstrate that the sharp decline in house prices during the Great Recession did not limit labor mobility. More likely than not, a dearth of job postings was the biggest barrier to finding jobs, but this article does not provide direct evidence on this.

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TABLE 1: DESCRIPTIVE STATISTICS: REGRESSION SAMPLE

Variable	Mean	Std. Dev.
Move CBSA	1.15	10.66
Equity $<= -20\%$	0.04	0.20
Equity $(-20, 0]\%$	0.12	0.32
Equity $[0, 20)\%$	0.32	0.47
Equity $>= 20\%$	0.52	0.50
Neg. shock (to local unemp. rate)	0.55	0.50
Neg. shock $\times$ Equity $<= -20\%$	0.04	0.19
Pos. shock $\times$ Equity $<= -20\%$	0.01	0.07
Neg. shock $\times$ Equity $(-20, 0)\%$	0.08	0.27
Pos. shock $\times$ Equity $(-20, 0)\%$	0.04	0.19
Neg. shock $\times$ Equity $[0, 20)\%$	0.27	0.44
Pos. shock $\times$ Equity $[0, 20)\%$	0.26	0.44
Neg. shock $\times$ Equity $>= 20\%$	0.17	0.37
Pos. shock $\times$ Equity $>= 20\%$	0.15	0.36
Lagged change in equity	0.06	0.12
Dummy for nonrecourse	0.40	0.49
Prime mortgage	0.21	0.41
Alt-A mortgage	0.34	0.47
Subprime mortgage	0.44	0.50
Investment purpose	0.02	0.15
Short-term hybrid	0.22	0.42
Subprime score	0.24	0.43
Mortgage balance	12.36	0.72
Home value	12.69	0.80
Neg. shock $\times$ Equity $< 0\%$	0.11	0.32
Pos. shock $\times$ Equity $< 0\%$	0.04	0.20
Neg. shock $\times$ Home value	6.98	6.36
Pos. shock $\times$ Home value	5.71	6.31
Neg. shock $\times$ Mortgage balance	6.81	6.21
Pos. shock $\times$ Mortgage balance	5.55	6.12

Notes: "Moved CBSA" is a dummy variable that equals 100 if an individual moved to another CBSA since the previous year. The 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 indices from CoreLogic). "Neg. shock (to local unemp. rate)" is a dummy variable that equals one if the difference between the annual change in the CBSA unemployment rate and the national average change is positive. "Dummy for nonrecourse" is a dummy variable that equals one if a borrower lived in a nonrecourse state during the year $t-1$. "Prime," "Subprime," and "Alt-A mortgage" are dummy variables that equal one if a mortgage is of a certain risk type, based on the classification by 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. "Subprime score" is a dummy variable that equals one if a borrower had a credit score lower than 641. "Near prime score" is a dummy variable that equals one if a borrower had a credit score between 640 and 699. "Mortgage" balance is the logarithm of the outstanding mortgage balance, while "Home value" is the logarithm of the value of the home imputed from initial value (deduced from borrowing LTV and original mortgage amount) adjusted for ZIP code housing appreciation. All listed variables except for moving rates have been lagged one year for the analysis.

Table 2: Probability of moving to another location

	CBSA		State	CBSA
	All		All	Prime non-jumbo
	(1)	(2)	(3)	(4)
Neg. shock × Equity <= −20%	1.48***	1.39***	0.79***	1.74***
	(24.01)	(18.89)	(17.87)	(4.74)
Neg. shock × Equity $(-20, 0]$%	0.52***	0.44***	0.31***	0.91***
	(15.01)	(10.64)	(12.10)	(4.34)
Neg. shock × Equity $[0, 20)$%	excluded group	excluded group	excluded group	excluded group
Neg. shock × Equity >= 20%	–0.16***	–0.12***	–0.11***	–0.39***
	(–5.77)	(–3.88)	(–5.39)	(–2.76)
Pos. shock × Equity <= −20%	1.07***	1.21***	0.93***	1.68***
	(8.58)	(8.42)	(8.80)	(3.04)
Pos. shock × Equity $(-20, 0]$%	0.48***	0.44***	0.37***	1.05***
	(10.67)	(8.05)	(9.54)	(3.72)
Pos. shock × Equity $(-20, 0]$%	excluded group	excluded group	excluded group	excluded group
Pos. shock × Equity >= 20%	0.07**	0.06	–0.02	–0.30*
	(2.04)	(1.56)	(–0.58)	(–1.70)
Lagged change in equity		–1.63***		
		(–9.47)		
ZIP × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	9,384,908	6,917,601	9,337,183	648,440
No. clusters	5,629	5,627	5,626	5,325

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment in a CBSA/state and the four equity dummies are variables for the amount of home equity at time $t-1$. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × year fixed effects, and ν_i are individual fixed effects. See Section 3.3 for a detailed variable description. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table 3: Probability of Moving to Another CBSA. The Role of home value and Mortgage Size

	(1)	(2)	(3)
Neg. shock	1.86***	0.75***	0.61**
	(6.91)	(2.69)	(2.16)
Neg. shock × Home value	–1.62***	–1.73***	–1.24***
	(–12.56)	(–12.92)	(–9.70)
Neg. shock × Mortgage balance		1.58***	1.32***
		(11.92)	(10.17)
Neg. shock × Equity < 0%			0.54***
			(14.54)
Pos. shock × Home value	–1.48***	–1.27***	–0.91***
	(–11.51)	(–10.47)	(–7.70)
Pos. shock × Mortgage balance		1.16***	1.03***
		(8.81)	(7.87)
Pos. shock × Equity < 0%			0.38***
			(8.42)
Individual effects	Y	Y	Y
Year effects	Y	Y	Y
No. obs.	9,384,919	9,353,088	9,353,088
No. clusters	5,631	5,631	5,631

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to CBSAs's unemployment rates. μ_{t-1} are year fixed effects, and ν_i are individual fixed effects. Home value and mortgage balance are log transformed. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10]% level.

Table 4: Benchmark Calibration Parameters

Preferences	
	Cobb-Douglas utility; 0.12 weight for housing.
	Discount rate 3.75 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).
	Non-local job offer probability 9.5 percent, 1 percent permanent income decrease.
	No job offer probability 5 percent.
	Employed:
	Unemployment shock probability 5 percent.
	Non-local job offer probability 5 percent, 1 percent permanent income increase.
	No change probability, 90 percent.
	Pension: 50 percent of last working period permanent income.
Interest rates	
	4 percent for deposits; 4.5 percent for mortgages.
	No uncertainty.
Housing Market	
	Down payment 5 percent.
	Buying cost 2 percent.
	Selling cost, age dependent (min 0.03, max 0.06). $\chi = 0.01 + 0.02 \times (1 + \text{age})^{0.295}$.
	Foreclosure: income (house) [deposits] one-time cost 15.5 (2.5) [2.5] percent.
Taxes	
	Proportional taxation.
	Income tax rate 20 percent (TAXSIM); mortgage interest fully deductible.
House Prices	
	Mean reverting. See discussion of equation (4) on text.
	Housing depreciation: owners, 1.5 percent; renters, 2.5 percent
	Rent-to-price ratio 6.9 percent.
Other	
	Warm-glow bequest motive.
	Exogenous moving probability: 2 percent.

Table 5: Model. Effect of Equity in Weak of Strong Labor Markets (Owners with Positive Mortgage Balance, Aged 25–60)

	Predicted equity		Actual equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	1.35***	0.80**	5.33***	5.32***
	(4.05)	(2.21)	(6.94)	(6.88)
Local Weak × Equity $(-20, 0)\%$	0.95***	0.67***	2.70***	2.71***
	(4.13)	(2.68)	(8.59)	(8.60)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.18	0.08	–0.57*	–0.63**
	(–0.92)	(0.39)	(–1.99)	(–2.03)
Local Strong × Equity $\leq -20\%$	1.04***	0.49	4.54***	4.53***
	(3.39)	(1.50)	(5.91)	(5.91)
Local Strong × Equity $(-20, 0)\%$	0.60**	0.31	2.37***	2.38***
	(2.50)	(1.19)	(7.20)	(7.20)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	–0.11	0.15	–0.15	–0.21
	(–0.54)	(0.70)	(–0.75)	(–0.97)
Lagged change in equity		–2.52***		0.13
		(–3.16)		(0.92)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	190,021	190,021	190,021	190,021
No. clusters	54	54	54	54

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, 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 listed in the first column. $D_{zt-1} \times \mu_{t-1}$ is the product of (lagged) region fixed effects and time fixed effects, and ν_i are individual fixed effects. Local weak regions and local strong regions differ in the intensity of local versus non-local job offers (80 percent and 90 percent, respectively). Robust standard errors are clustered by region. *** (**) [*] significant at the 1 (5) [10] percent level. Results are for the Great Recession calibration described in Section 4.3.

Table 6: Model. The Role of Variables with Empirical Counterparts: Home Value and Mortgage Size

	Actual home value and equity			Predicted
	(1)	(2)	(3)	(4)
Local Weak × Home value	–4.01***	–3.98***	–1.28*	–2.11***
	(–5.32)	(–5.27)	(–1.97)	(–2.96)
Local Weak × Mortgage balance		0.14***	0.09*	0.15***
		(2.87)	(1.70)	(3.05)
Local Weak × Equity< 0			3.21***	1.09***
			(9.82)	(4.69)
Local Strong × Home value	–1.44*	–1.41*	1.08	0.30
	(–1.95)	(–1.90)	(1.66)	(0.38)
Local Strong × Mortgage balance		0.03	–0.02	0.03
		(0.75)	(–0.54)	(0.91)
Local Strong × Equity< 0			3.01***	0.88***
			(8.51)	(4.31)
Year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	190,129	190,129	190,129	190,129
No. clusters	54	54	54	54

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise; X is a vector of (lagged) regressors listed in the first column of the table. μ_{t-1} is a time fixed effect, and ν_i is an individual fixed effect. Home values and mortgage balances are log transformed. *** (**) [*] significant at the 1 (5) [10] percent level.

Table 7: Model. The Role of Important State Variables and Foreclosure in Moving Decisions

	Actual					Predicted		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Weak × Home value	–1.28*	–1.07*	–0.65	–0.63	–0.21	–2.11***	–1.40**	–0.87
	(–1.97)	(–1.69)	(–1.07)	(–1.03)	(–0.34)	(–2.96)	(–2.13)	(–1.30)
Local Weak × Mortgage balance	0.09*	–0.12*	0.06	0.05	0.10*	0.15***	–0.00	0.10*
	(1.70)	(–1.97)	(1.11)	(0.96)	(1.77)	(3.05)	(–0.07)	(1.80)
Local Weak × Equity< 0	3.21***	2.94***	3.11***	2.63***	–0.64**	1.09***	0.38*	–0.78***
	(9.82)	(9.16)	(9.31)	(8.46)	(–2.20)	(4.69)	(1.96)	(–4.36)
Local Weak × Deposits		1.58***	–0.25	–0.16	–0.85**		0.68*	–0.91***
		(4.07)	(–0.71)	(–0.47)	(–2.63)		(1.90)	(–2.76)
Local Weak × Permanent income		0.04	–0.03	–0.04	1.12		0.18	1.13
		(0.04)	(–0.04)	(–0.04)	(1.21)		(0.19)	(1.23)
Local Weak × Unemployed			11.65***	10.76***	10.69***		10.18***	10.11***
			(26.75)	(22.00)	(22.77)		(22.33)	(23.12)
Local Weak × Equity< 0 × Unemployed				6.41***	4.89***		10.68***	9.55***
				(3.56)	(2.71)		(6.18)	(5.61)
Local Weak × Foreclosed					6.34***			6.18***
					(16.97)			(15.35)
Local Strong × Home value	1.08	0.98	1.19*	1.22*	1.60**	0.30	0.46	0.76
	(1.66)	(1.57)	(1.93)	(1.97)	(2.59)	(0.38)	(0.63)	(1.04)
Local Strong × Mortgage balance	–0.02	–0.05	0.05	0.04	0.07**	0.03	–0.01	0.07**
	(–0.54)	(–1.38)	(1.48)	(1.33)	(2.08)	(0.91)	(–0.45)	(2.10)
Local Strong × Equity< 0	3.01***	3.00***	3.10***	2.87***	0.44*	0.88***	0.58***	–0.35**
	(8.51)	(8.41)	(8.51)	(8.80)	(1.75)	(4.31)	(3.26)	(–2.42)
Local Strong × Deposits		0.21	–0.53***	–0.50***	–0.98***		0.34*	–0.95***
		(1.21)	(–3.27)	(–3.06)	(–6.00)		(1.82)	(–6.00)
Local Strong × Permanent income		–0.96	–0.79	–0.82	0.01		–0.31	0.36
		(–1.66)	(–1.36)	(–1.40)	(0.02)		(–0.54)	(0.65)
Local Strong × Unemployed			4.74***	4.36***	4.34***		4.02***	4.02***
			(10.62)	(8.93)	(8.90)		(9.29)	(9.36)
Local Strong × Equity< 0 × Unemployed				3.17**	2.09		5.42***	4.52***
				(2.33)	(1.56)		(4.15)	(3.43)
Local Strong × Foreclosed					4.70***			5.05***
					(10.70)			(10.07)
No. obs.	190,129	190,129	190,129	190,129	190,129	190,129	190,129	190,129
No. clusters	54	54	54	54	54	54	54	54

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + \mu_{t-1} + \nu_i + u_{it}$, 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 (lagged) regressors listed in the first column of the table. μ_{t-1} is a time fixed effect, and ν_i is an individual fixed effect. Home value, mortgage balance, deposits and permanent income are log transformed. In columns (5) and (8), a dummy for foreclosure between period $t-1$ and t is added.

Table 8: Model. Mobility of the Old and the Young

	Actual		Predicted	
	Young	Old	Young	Old
	(1)	(2)	(3)	(4)
Local Weak × Home value	–1.86	0.22	–1.67	–1.75**
	(–1.29)	(0.31)	(–1.16)	(–2.67)
Local Weak × Mortgage balance	0.81***	0.05	0.81***	–0.01
	(6.39)	(0.57)	(6.47)	(–0.16)
Local Weak × Equity< 0	1.60***	3.60***	0.17	–0.33
	(5.60)	(3.98)	(0.61)	(–1.21)
Local Weak × Deposits	–0.41	–0.71	0.19	0.18
	(–1.29)	(–1.05)	(0.71)	(0.24)
Local Weak × Permanent income	1.14	–0.33	1.80	–1.53
	(0.78)	(–0.35)	(1.18)	(–1.41)
Local Weak × Unemployed	10.65***	11.07***	8.81***	11.46***
	(12.22)	(12.55)	(8.95)	(13.68)
Local Weak × Equity< 0 × Unemployed	7.98***	6.37**	13.12***	4.76
	(3.20)	(2.06)	(6.25)	(0.97)
Local Strong × Home value	1.43	1.79**	0.56	0.19
	(1.06)	(2.58)	(0.39)	(0.25)
Local Strong × Mortgage balance	0.33***	0.02	0.45***	–0.03
	(2.94)	(0.58)	(4.49)	(–0.78)
Local Strong × Equity< 0	2.35***	3.52***	0.48*	0.02
	(8.25)	(3.91)	(1.94)	(0.07)
Local Strong × Deposits	–0.84***	–0.45	–0.08	0.28
	(–3.08)	(–1.35)	(–0.28)	(0.91)
Local Strong × Permanent income	–0.81	–0.57	0.30	–1.34**
	(–0.78)	(–1.01)	(0.27)	(–2.26)
Local Strong × Unemployed	4.79***	4.36***	4.29***	4.11***
	(4.77)	(9.22)	(4.28)	(8.47)
Local Strong × Equity< 0 × Unemployed	4.98**	–1.06	5.78***	3.97
	(2.56)	(–0.51)	(3.07)	(1.07)
Year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	95,194	94,935	95,194	94,935
No. clusters	54	54	54	54

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. μ_{t-1} is a time fixed effect, and ν_i is an individual fixed effect. Home value, mortgage balance, deposits and permanent income are log transformed. Separate regressions are run for the young (ages 25–45) and the old (ages 46–60). *** (**) [*] significant at the 1 (5) [10] percent level.

Table 9: Counterfactual Moving Simulation: No Foreclosure

	Actual		Predicted	
	(1)	(2)	(3)	(4)
Local Weak × Home value	–0.59	–0.09	–0.85*	–0.07
	(–1.44)	(–0.21)	(–1.68)	(–0.14)
Local Weak × Mortgage balance	–0.06	0.13**	–0.05	0.11*
	(–1.39)	(2.07)	(–1.24)	(1.78)
Local Weak × Equity< 0	1.00***	0.45**	0.47**	0.00
	(4.03)	(2.40)	(2.39)	(0.02)
Local Weak × Deposits		–1.35***		–1.09***
		(–3.78)		(–3.18)
Local Weak × Permanent income		0.55		0.83
		(0.80)		(1.24)
Local Weak × Unemployed		10.18***		9.72***
		(15.20)		(13.58)
Local Weak × Equity< 0 × Unemployed		11.98***		10.38***
		(5.31)		(4.54)
Local Strong × Home value	1.21**	1.14**	0.90	1.10*
	(2.55)	(2.29)	(1.63)	(1.93)
Local Strong × Mortgage balance	0.06	0.22***	0.06	0.20***
	(1.31)	(4.74)	(1.35)	(4.49)
Local Strong × Equity< 0	0.85***	0.41***	0.35**	0.07
	(4.57)	(2.79)	(2.63)	(0.56)
Local Strong × Deposits		–1.37***		–1.17***
		(–6.12)		(–5.28)
Local Strong × Permanent income		1.48***		1.82***
		(3.20)		(3.90)
Local Strong × Unemployed		4.80***		4.72***
		(14.90)		(15.88)
Local Strong × Equity< 0 × Unemployed		8.22***		5.08***
		(4.61)		(3.94)
Year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	182,495	182,495	182,495	182,495
No. clusters	54	54	54	54

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. μ_{t-1} is a time fixed effect, and ν_i is an individual fixed effect. Home value, mortgage balance, deposits and permanent income are log transformed. *** (**) [*] significant at the 1 (5) [10] percent level.

Figure 1: Distribution of Negative Equity by State.

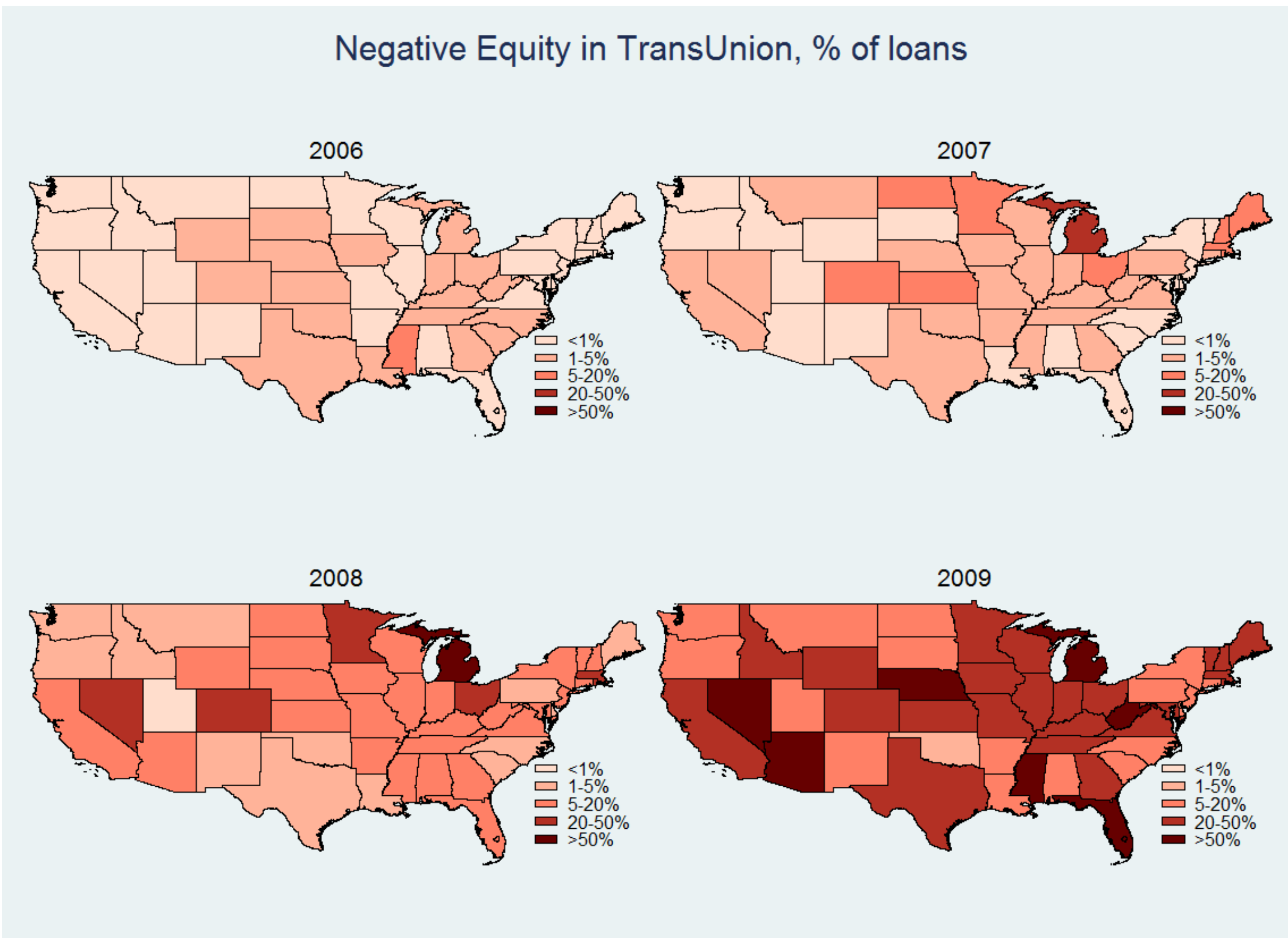
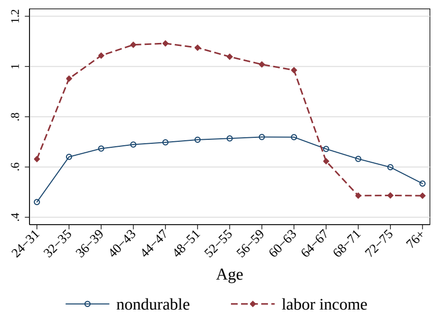
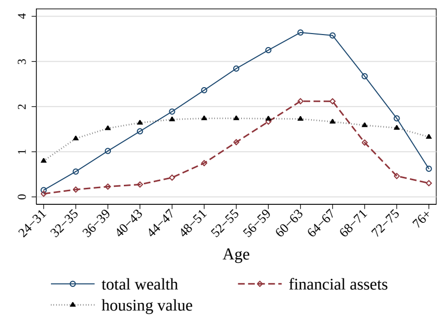


Figure 2: The Benchmark and the Data.

Predicted Life-cycle profiles of income, consumption, and assets



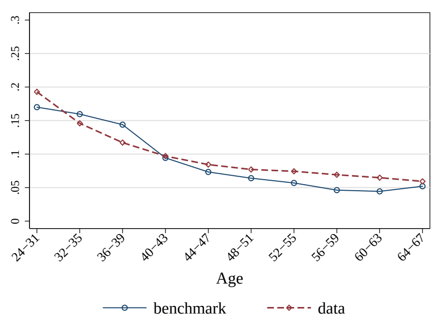
(a) Income and Consumption



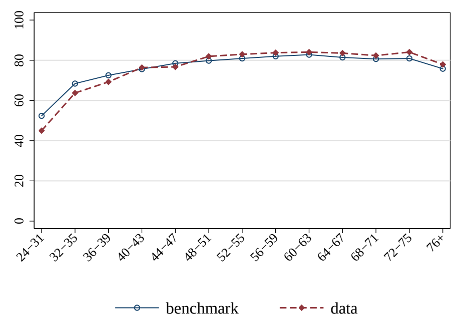
(b) Mean Wealth

Match of Life-cycle profiles to the data.

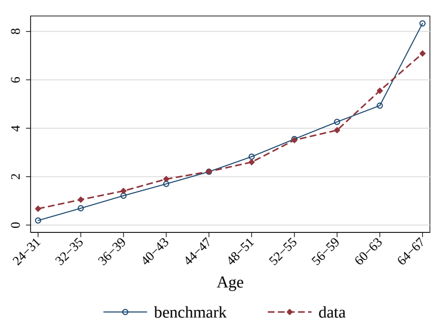
Data from the Survey of Consumer Finances (1989–2004), except moving rates from Equifax (1999–2008).



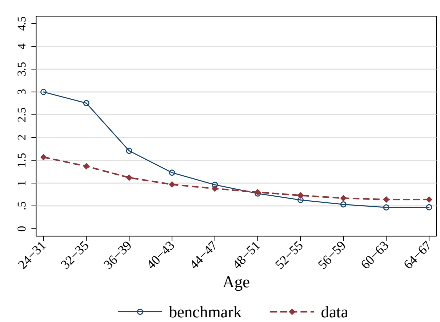
(c) Moving Rate



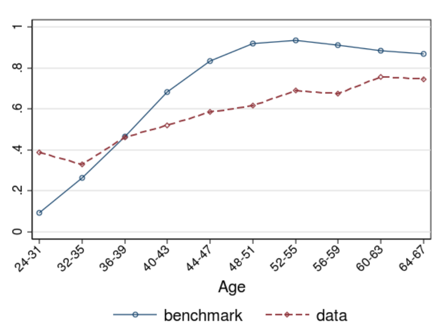
(d) Homeownership



(e) Median Wealth/Earnings Ratio



(f) Median Housing Value/Wealth Ratio



(g) Home Equity

(Online Appendices)

A More Details on the Data and Data Cleaning

The TU-LP dataset was created by TransUnion who merged credit report data with mortgage information from the LoanPerformance Securities Database from CoreLogic.[36]

We start with a TU-LP merged sample for the years 2005–2007 with approximately 47.3 million observations (11.8 million first-lien loans and 13.1 million borrowers). We drop loans for which the loan-to-value ratio is missing (less than 1 percent of loans), and we drop borrowers that do not have matching ZIP code-level HPI in the CoreLogic dataset (11 million observations).[37] We further drop all borrowers who had more than one active first lien reported within a year (9 million observations).

After calculating lagged variables, we keep data for the years 2007–2009, which leaves us with 17 million observations (including 4.8 million loans and 6.6 million borrowers). The main cleaning restrictions applied to this sample are the following: (1) we drop 4.3 million 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 that the property is not owner-occupied. (2) We drop 800,000 observations for which the balance-to-limit ratio on all mortgages is either zero or missing. This eliminates borrowers who terminated their loan at time $t-1$, as those are either renters at time $t-1$ or homeowners who have paid off their mortgages. (3) We

[36] The exact matching algorithm is proprietary, 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 (93 percent with less than 1 percent false-positive for open loans, and 73 percent for closed loans).

[37] The CoreLogic HPI dataset covers 19.25 percent of the ZIP codes in the U.S.; these ZIP codes cover about 62 percent of the U.S. population.

drop 81,000 individuals who default on their mortgage despite having more than 20 percent equity in their homes—this eliminates individuals for whom measurement error in equity is likely to be substantial. These restrictions leave us with approximately 12 million observations (4 million loans and 5.6 million borrowers). In our regressions, we do not utilize 1.6 million individuals that appear in our data only once (singletons). Dropping observations for which any variable used in the main regression is missing, leaves us with about 9 million observations. This sample contains loans with single borrowers or with multiple co-borrowers. We drop loans with more than two co-borrowers (0.18 percent of the sample). For all empirical tables reported in the paper and appendices we keep loans with one or two co-borrowers (about 2 million loans have single borrowers and about one million loans have two co-borrowers). For robustness (not reported in a table), we re-estimate Table 2 using a sample that includes all single borrowers and only one co-borrower (selected randomly) from each pair; the results are not affected by this selection.

Most of the mortgages in our sample are classified as subprime or Alt-A.[38] Also, as Demyanyk and Van Hemert (2011) show, more than half of the sample consists of so-called hybrid loans, for which the interest rate is fixed for two or three years and then starts adjusting. (Loans that reset so quickly are nonexistent in the prime market). These hybrid mortgages were short-lived, with

[38]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 below 650), more than 50 percent have prepayment penalties, and loans are often 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 LTV 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 FICO score higher than the 620 average.

almost all of them being in default or prepaid within three years of origination (see, for example, Demyanyk, 2009), and they were more likely than prime mortgages to generate negative equity because they typically were originated with very low down payments.

B Discussion of Identification with Individual and ZIP×Year Fixed Effects

Because we include individual fixed effects, our results are not driven by constant individual-specific characteristics (for example, high impatience, which may simultaneously result in high mobility and low home equity). Inclusion of an individual-specific fixed effect is equivalent to removing the individual-specific average. Consider, for example, the dummy for very negative equity in year t and refer to the dummy as D_{it}^N, where individual i is in the sample for T_i periods, and label the CBSA-specific, positive-shock dummy $P_{rt} = \mathbb{1}(\text{Shock}_{rt}^u < 0)$ (relatively lower local unemployment shock). Keeping in mind that agents in our sample do not refinance until they drop out of the sample in the last period, the individual-level variation identifying this regressor, when individual fixed effects are included, is:

$$D_{it}^N P_{rt} - \frac{1}{T_i}\sum_{t=1}^{T_i} D_{it}^N P_{rt} = D_{it}^N - \frac{1}{T_i}\sum_{t=1}^{T_i} D_{it}^N \tag{A-1}$$

for the (majority of) cases where the CBSA labor market dummy does not change ($P_{rt} = 1$). This case illustrates the most important variation in the data (for individuals in weak labor markets the situation is similar). It is clear then that our results are mainly identified from individuals whose equity is not in the same category each year. Because the sample is constructed so that individuals do not refinance (except in the final year of their tenure in the sample which does not show up in the lagged regressors), the variation in the exogenous individual-specific equity dummy is driven only by ZIP code price variation, which affects individuals differently according to their initial LTV. Identification rests on the assumption that any component of the innovation term in the mobility equation is uncorrelated with this demeaned term.[39] We consider this assumption reasonable because individuals drop out of the sample the year after they move (and right-hand-side variables are all measured in the year before the move), which rules out the possibility that individuals select themselves into appreciating (or depreciating) ZIP codes during the time they are observed. Changes in local labor market conditions will also provide some identification due to interactions with the individual fixed effects, but this is likely to be of second-order importance because consumers are in the sample for only a few years.

The inclusion of ZIP $\times$ year fixed effects implies, in addition, that each equity regressor is identified from variation relative to its average value across the N_{zt} individuals in the ZIP code where an individual lives in a given year. Consider

$$D_{it}^N P_{rt} - \frac{1}{N_{zt}} \sum_{i=1}^{N_{zt}} D_{it}^N P_{rt} = D_{it}^N - \frac{1}{N_{zt}} \sum_{i=1}^{N_{zt}} D_{it}^N, \tag{A-2}$$

where, again, we assume that P_{rt} equals one. The regressor (apart from controlling for individual-specific components) is identified from the difference between the negative equity dummy and the share of people with negative equity in the ZIP code in year t. Our results are therefore not driven by any average differences between ZIP codes. For example, some ZIP codes may be preferred by young people with high mobility and such ZIP codes might have lower than average appreciation, and in the absence of the ZIP code dummies

[39]An individual-specific unobserved component will be removed by the demeaning. Consider again D_{it}^N, which is our main regressor of interest, although the following holds for any regressor. D_{it}^N can be approximated by components in the manner $D_{it}^N = w_i + v_{it}$, where w_i captures inherent individual-specific traits and v_{it} captures other variation that is not a function of inherent traits. The demeaning clearly removes the w_i component. (Age is an important time-varying individual-specific factor, but it is absorbed by the combination of the individual fixed effect with ZIP $\times$ year fixed effects.) It also removes the average of the v_{it}-term, which can be seen as "collateral damage," most obviously in the case where individuals are in the sample for only one period and all variation is removed. Simulated data, used in the model section, do not feature any w_i component by design; we, however, also include individual fixed effects in the regressions on our simulated data so that the treatment of the v_{it}-term in the simulated data will be the same as in the empirical data.

we might spuriously assign differences between ZIP codes to equity effects on individual mobility.[40]

C Supplementary Empirical Results

In this appendix, we display several supplementary results using the empirical data to further establish the robustness of our results.

Table C-1 shows that moving rates declined substantially from 2007 to 2009. We present statistics from TU-LP, from an Equifax sample similarly constructed (consumers with positive balances on their mortgages), and from the CPS.[41] As shown in the top two panels of Table C-1, the overall moving rate, computed as a change in ZIP code, declined from approximately 6.5 percent to 5.8 percent for TU-LP households, and from 4.3 percent to 3.6 percent for Equifax households. The moving rate across CBSAs declined from about 2.3 percent to 1.8 percent in TU-LP, and from 1.5 percent to 1.2 percent in Equifax. The moving rate from one state to another declined from 1.6 percent to 1.1 percent in TU-LP, and from 1.1 percent to 0.8 percent in Equifax. TU-LP households are predominantly subprime borrowers, which might explain why moving rates differ across the two datasets.[42] In the bottom panel, we tabulate moving rates for homeowners using the CPS, which has much broader

[40]In a balanced panel, the regressions can be performed literally by subtracting the individual and ZIP-year averages sequentially, but this no longer holds in unbalanced panels (see Wansbeek and Kapteyn, 1989). We ran the regressions using the REGHDFE module in Stata (`https://ideas.repec.org/c/boc/bocode/s457874.html`) after verifying that it handles multiple fixed effects correctly in our unbalanced sample.

[41]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 U.S. individuals who have a social security number and use credit in some form. For a more detailed description of the data, see Lee and van der Klaauw (2010). A previous version of this paper studied mobility in relationship to house-price appreciation using this dataset in addition to the TU-LP data. The results were consistent with the ones reported to the extent they can be compared, but for brevity we focus our regressions on TU-LP data only.

[42]The moving rates in Equifax are in line with the national moving rates for homeowners reported, for example, in Molloy, Smith, and Wozniak (2011). Higher moving rates in TU-LP could be due to higher risk tolerance of homeowners with non-standard mortgages, and higher mobility of more risk-tolerant individuals across labor markets (see Dohmen et al. 2010 for some evidence on the latter).

coverage than the credit bureaus; for example, it includes very young, highly mobile people who may not yet have a credit history, military personnel, and owners with zero mortgage balances, whom we do not include in our empirical work. Nonetheless, the CPS, in spite of its very different sampling frame, confirms the temporal patterns observed in TU-LP and Equifax.

Table C-2 shows correlations for the variables in our regressions with individual and ZIP $\times$ year fixed effects removed. This is informative about how closely our regressors are correlated after the demeaning that is implicitly done by the regression algorithm when fixed effects are included. Our demeaned regressors are not very correlated with the exception of the change in equity, which correlates quite highly with the equity categories.

Table C-3 examines if our results are specific to certain types of mortgages. We compare our results to those for all mortgages combined, in column (1) of Table 2. Scanning the results, the general pattern regarding equity and mobility found in Table 2 holds up. The first column uses a sample of prime jumbo loans, and the results are very similar for this group, even if this sample comprises individuals who are quite different from those in the subprime or non-jumbo prime samples. In the second column, labeled "Subprime," we report the results for the sample of consumers with subprime mortgages only. The results are very similar. The next column considers individuals with Alt-A loans: the mobility patterns are similar to those found in the subprime sample. In the column "Subprime score," we focus on individuals with a credit score below 641 in the first year they are observed and find results similar to results in the previous columns. In the column labeled "No invest.," we drop homes purchased for investment. The results are virtually unchanged from the corresponding column of Table 2, 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 C-4 examines robustness along other dimensions while focusing on CBSA mobility for the full 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.[43] The results are again similar to those found earlier, except that we find a slightly higher mobility of individuals with very positive equity, compared with those with moderately positive equity, in CBSAs with positive labor market shocks, but the mobility of these individuals is still lower than for those with highly negative equity. In the second column, we use the number of vacancies in the CBSA to measure local labor market conditions. We define dummy variables similarly defined as the ones for change in unemployment (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). The results are similar to our baseline results with slightly smaller estimated coefficients. The results in the third column, using employment growth in the CBSA as the measure of local labor market conditions are also very similar.

Table C-5 departs from the main regression of Table 2 by adding more equity categories. In weak and strong labor markets, we find a monotonic decline in the propensity to move CBSAs with increasing equity. The pattern of higher mobility of households with low equity is robust and mobility is nearly monotonically declining in equity. We conclude that our results are not caused by having a small number of equity categories.

Table C-6 examines the case of three types of labor markets where "Rel. High Unemp." is a dummy taking a value of one, if the change in unemployment is 0.5 percentage points or more higher than the average across CBSAs, "Rel. Low Unemp." refers to the case of 0.5 percentage points less than the average change, and the average group are the remaining CBSAs. (The cut-offs are chosen to obtain groups of similar size.) The pattern of higher mobility of low-equity individuals remains significant. There is no lock-in in any of the labor-market groups but the tendency for low equity households be-

[43] 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. Ghent and 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 whether this result holds up for our sample period, but the Great Recession may well be atypical in this dimension due to the very large number of defaults.

comes weaker when the labor market becomes stronger. This is intuitive and is reflected in the regressions on simulated data—in particular, when directly considering employed versus unemployed—so we conclude that the inclusion of more labor markets does not cast doubt on our conclusions. It should be kept in mind that our regressions capture only whether low-equity individuals are more likely to move than high-equity individuals—they do not capture whether people on average are more likely to stay in strong labor markets.

Table C-7 repeats the estimations of Table 3 including ZIP $\times$ year fixed effects. The results for the empirical regressions are quite similar whether ZIP $\times$ year fixed effects are included or not.

Table C-8 shows that our results are robust to controlling for credit scores. We define "Credit score" as TransUnion's VantageScore, which has a range from 501 to 990. We create "Subprime score" and "Near prime score" dummy variables equal to one if the VantageScore takes values below 641, and between 641 and 700, respectively. Individuals with low scores are more likely to move CBSA and because a low score is correlated with negative equity, the coefficients to negative equity become a little smaller, but they remain highly significant.[44] The third column of Table C-8 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 qualitatively similar to the results of Table 2, in which the regressions, properly, we argue, include individual fixed effects. In column (3), the coefficients on "Subprime score" and "Near prime score" turn negative and the coefficient to lagged change in equity turns positive. This illustrates that "permanent" differences between individuals can correlate quite differently with the dependent variable than the individual-level changes over time that are isolated by including fixed effects. Our conjecture is that more-educated individuals are more mobile and also have higher scores, but having established that our main result of interest is robust, we do not explore this issue further.

[44] A study by VantageScore 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/`.

The results tabulated in Table C-9 are from regressions similar to our main regressions in Table 2 but they include CBSA $\times$ year fixed effects instead of ZIP $\times$ year fixed effects. The results are quite similar to those reported in the main text, with slightly less significant coefficients. Mechanically, the interpretation is that changes in equity relative to the average in the ZIP code (in a given year) correlates more with mobility than the change in equity relative to the average in the CBSA. One might have expected the latter to be more significant, as less variation is absorbed, but we do not explore this issue further.

In Table C-10, we repeat the main regression of Table 2 using current equity as reported by CoreLogic in their TrueLTV dataset.[45] Current equity is likely endogenous to mobility (why pay on a mortgage, if one has decided to walk away from the house in the near future?), and because CoreLogic does not perform property-level appraisals, except at origination, we believe the estimates contain significant measurement error. These results are, therefore, presented only for "full disclosure," but the finding of relatively high mobility for households with very negative equity remains robust in weak labor markets, although high-equity individuals are also more likely to move in strong labor markets.

[45] CoreLogic matched mortgages found in the 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 C-1: Moving Rates (percent)

Year	ZIP	CBSA	State
TransUnion, TU-LP			
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, CPS			
Year	County	CBSA	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

Notes: The table shows moving rates calculated from 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 for the credit bureau data, and the fraction of homeowners who moved from one county to another for the CPS, because ZIP code identifiers are not available in the CPS. The second column shows the fraction of homeowners who moved to a different CBSA. The third column shows moving rates from one state to another. The rates have been multiplied by 100 to yield percentages.

TABLE C-2: CORRELATION MATRIX. REGRESSION SAMPLE
ZIP × YEAR AND INDIVIDUAL FIXED EFFECTS REMOVED

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Move CBSA	1.00													
(2)	Neg. shock × Equity <= −20%	0.03	1.00												
(3)	Pos. shock × Equity <= −20%	0.00	−0.03	1.00											
(4)	Neg. shock × Equity $(-20, 0)$%	0.01	−0.22	−0.05	1.00										
(5)	Pos. shock × Equity $(-20, 0)$%	0.00	−0.09	−0.12	−0.08	1.00									
(6)	Neg. shock × Equity >= 20%	0.01	0.09	−0.02	−0.08	−0.08	1.00								
(7)	Pos. shock × Equity >= 20%	−0.01	−0.12	−0.03	−0.12	−0.05	−0.45	1.00							
(8)	Lagged change in equity	−0.03	−0.42	−0.09	−0.25	0.00	−0.03	0.38	1.00						
(9)	Neg. shock × Home value	0.02	0.23	−0.07	0.26	−0.24	0.54	−0.61	−0.44	1.00					
(10)	Pos. shock × Home value	−0.02	-0.25	0.07	−0.28	0.22	−0.50	0.65	0.45	−0.99	1.00				
(11)	Neg. shock × Mortgage balance	0.02	0.24	−0.07	0.27	−0.24	0.52	−0.61	−0.45	1.00	−0.99	1.00			
(12)	Pos. shock × Mortgage balance	−0.02	−0.25	0.07	−0.28	0.23	−0.49	0.64	0.45	−0.99	1.00	−0.99	1.00		
(13)	Neg. shock × Equity < 0%	0.01	−0.11	0.01	0.12	0.04	−0.05	0.30	0.42	−0.32	0.34	−0.32	0.33	1.00	
(14)	Pos. shock × Equity < 0%	0.01	0.03	−0.11	0.02	0.13	0.19	0.00	0.06	0.21	−0.20	0.21	−0.20	−0.08	1.00

Notes: The table shows correlation coefficients for the variables used in the regression analysis. "Moved CBSA" is a dummy variable that equals 100 if an individual moved to another CBSA since the previous year. "Neg. shock" ("Pos. shock") is a dummy variable that equals one if the difference between the annual change in the CBSA unemployment rate and the national average change is positive (negative). These dummy variables are interacted with dummies for the amount of predicted equity an individual has in the period when the moving decision is made. Mortgage balance is the logarithm of the outstanding mortgage balance, while Home value is the logarithm of the home value of imputed from initial value (deduced from borrowing LTV and original mortgage amount) adjusted for ZIP code housing appreciation from origination to period $t-1$. "Lagged change in equity" is a change in predicted equity at time $t-1$ (all other regressors are measured at time $t-1$.

Table C-3: Probability of moving to another CBSA by Type of Mortgage

	Prime jumbo (1)	Subprime (2)	Alt-A (3)	Subprime score (4)	No invest. (5)	No invest. Nor hybrid (6)
Neg. shock × Equity <= −20%	1.66***	1.43***	1.60***	1.36***	1.39***	1.60***
	(5.54)	(15.25)	(13.42)	(10.93)	(18.84)	(18.12)
Neg. shock × Equity $(-20, 0]$%	0.69***	0.46***	0.50***	0.47***	0.43***	0.51***
	(4.88)	(8.67)	(7.66)	(6.73)	(10.41)	(10.45)
Neg. shock × Equity $[0, 20)$%	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock × Equity >= 20%	–0.52***	–0.11**	–0.25***	–0.10*	–0.13***	–0.25***
	(–5.34)	(–2.40)	(–4.50)	(–1.75)	(–3.87)	(–6.88)
Pos. shock × Equity <= −20%	2.18***	1.14***	1.42***	1.03***	1.20***	1.43***
	(3.68)	(5.78)	(6.32)	(4.49)	(8.32)	(8.86)
Pos. shock × Equity $(-20, 0]$%	0.69***	0.46***	0.50***	0.43***	0.43***	0.54***
	(2.68)	(7.06)	(5.06)	(5.62)	(7.89)	(7.97)
Pos. shock × Equity $[0, 20)$%	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Pos. shock × Equity >= 20%	–0.33**	0.00	0.04	0.03	0.06	–0.09*
	(–2.32)	(0.00)	(0.61)	(0.48)	(1.45)	(–1.93)
Lagged change in equity	–1.84***	–1.60***	–2.26***	–1.26***	–1.65***	–1.53***
	(–3.62)	(–7.48)	(–7.20)	(–4.92)	(–9.49)	(–7.74)
ZIP × year effects	Y	Y	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y	Y	Y
No. obs.	1,018,559	2,911,479	2,326,887	1,580,597	6,750,488	5,279,187
No. clusters	4,033	5,618	5,618	5,616	5,626	56,25

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment in a CBSA and the four equity measures are dummy variables for the amount of home equity at time $t-1$. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × year fixed effects, and ν_i are individual fixed effects. Column "Prime jumbo" refers to individuals who hold prime loans, the majority of which are jumbo loans. Column "Subprime" refers to individuals whose loans are labeled so by CoreLogic, while column "Alt-A" includes individuals who hold Alt-A loans, of which many are held by investors. Column "Subprime score" refers to individuals with a VantageScore less than 641, while 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). Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10]% level.

Table C-4: Moving to another CBSA. No-Recourse and Alternative Measures of Labor Market Shocks

	Non-recourse states (1)	All states, vacancy rates (2)	All states, empl. growth (3)
Neg. shock × Equity $<= -20\%$	1.26***	1.19***	1.14***
	(13.13)	(15.17)	(13.63)
Neg. shock × Equity $(-20, 0]\%$	0.33***	0.34***	0.29***
	(5.90)	(7.92)	(6.26)
Neg. shock × Equity $[0, 20)\%$	excluded group	excluded group	excluded group
Neg. shock × Equity $>= 20\%$	–0.15***	–0.09***	–0.03
	(–3.46)	(–2.93)	(–0.82)
Pos. shock × Equity $<= -20\%$	1.31***	0.82***	0.81***
	(4.18)	(5.03)	(5.58)
Pos. shock × Equity $(-20, 0]\%$	0.54***	0.21***	0.29***
	(3.49)	(3.64)	(5.32)
Pos. shock × Equity $[0, 20)\%$	excluded group	excluded group	excluded group
Pos. shock × Equity $>= 20\%$	0.41***	0.09**	0.20***
	(4.66)	(2.45)	(5.36)
Lagged change in equity	–1.64***	–1.48***	–2.08***
	(–6.50)	(–8.51)	(–12.38)
ZIP × year effects	Y	Y	Y
Individual effects	Y	Y	Y
No. obs.	2,904,674	5,541,584	6,917,601
No. clusters	1,656	3,974	5,627

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to CBSA's unemployment rates (first column), vacancy rates (second column) or employment growth (third column); the four equity measures are dummy variables for the amount of home equity at time $t-1$. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × year fixed effects, and ν_i are individual fixed effects. 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 TU-LP sample but CBSA's vacancy rates and employment growth rates, respectively, for construction of the labor market shocks. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10]% level.

Table C-5: Moving CBSA. More equity dummies

	(1)		(2)
Neg. shock × Equity $< -50\%$	2.36*** (12.64)	Pos. shock × Equity $[-40, -30)\%$	1.07*** (4.50)
Neg. shock × Equity $[-50, -40)\%$	1.53*** (9.97)	Pos. shock × Equity $[-30, -20)\%$	1.10*** (6.66)
Neg. shock × Equity $[-40, -30)\%$	1.23*** (10.76)	Pos. shock × Equity $[-20, -10)\%$	0.71*** (7.77)
Neg. shock × Equity $[-30, -20)\%$	0.79*** (9.16)	Pos. shock × Equity $[-10, 0)\%$	0.34*** (5.90)
Neg. shock × Equity $[-20, -10)\%$	0.50*** (7.50)	Pos. shock × Equity $[0, 10)\%$	excluded group
Neg. shock × Equity $[-10, 0)\%$	0.26*** (5.34)	Pos. shock × Equity $[10, 20)\%$	0.04 (0.96)
Neg. shock × Equity $[0, 10)\%$	excluded group	Pos. shock × Equity $[20, 30)\%$	0.03 (0.48)
Neg. shock × Equity $[10, 20)\%$	–0.13*** (–3.11)	Pos. shock × Equity $[30, 40)\%$	0.26*** (3.68)
Neg. shock × Equity $[20, 30)\%$	–0.14*** (–2.90)	Pos. shock × Equity $[40, 50)\%$	0.60*** (6.93)
Neg. shock × Equity $[30, 40)\%$	0.03 (0.52)	Pos. shock × Equity $\geq 50\%$	1.01*** (9.59)
Neg. shock × Equity $[40, 50)\%$	0.23*** (2.90)	Lagged change in equity	–1.43*** (–8.15)
Neg. shock × Equity $\geq 50\%$	0.54*** (5.60)		
Pos. shock × Equity $< -50\%$	2.76***	No. obs.	6,917,601
	(4.85)	No. clusters	5,627
Pos. shock × Equity $[-50, -40)\%$	1.35***	ZIP × year effects	Y
	(3.51)	Individual effects	Y

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. See Section 3.3 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × 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 C-6: Moving CBSA. All Loans.
More unemployment shock categories

	(1)	(2)
Rel. High Unemp. $\times$ Equity $\leq -20\%$	1.62*** (18.48)	1.44*** (16.25)
Rel. High Unemp. $\times$ Equity $(-20, 0)\%$	0.40*** (6.70)	0.35*** (5.80)
Rel. High Unemp. $\times$ Equity $[0, 20)\%$	excluded group	excluded group
Rel. High Unemp. $\times$ Equity $\geq 20\%$	–0.41*** (–9.41)	–0.35*** (–7.94)
Ave. Unemp. $\times$ Equity $\leq -20\%$	1.27*** (13.40)	1.13*** (11.83)
Ave. Unemp. $\times$ Equity $(-20, 0)\%$	0.47*** (11.02)	0.42*** (9.93)
Ave. Unemp. $\times$ Equity $[0, 20)\%$	excluded group	excluded group
Ave Unemp. $\times$ Equity $\geq 20\%$	0.05 (1.55)	0.10*** (2.95)
Rel. Low Unemp. $\times$ Equity $\leq -20\%$	0.79** (2.29)	0.67** (2.00)
Rel. Low Unemp. $\times$ Equity $(-20, 0)\%$	0.34*** (3.09)	0.29*** (2.62)
Rel. Low Unemp. $\times$ Equity $[0, 20)\%$	excluded group	excluded group
Rel. Low Unemp. $\times$ Equity $\geq 20\%$	–0.14** (–2.10)	–0.09 (–1.38)
Lagged change in equity		–1.58*** (–9.22)
ZIP $\times$ year effects	Y	Y
Individual effects	Y	Y
No. obs.	6,917,601	6,917,601
No. clusters	5,627	5,627

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Rel. High/Rel. Low/Ave. Unemp. are dummy variables that capture shocks to unemployment in a CBSA/state, which are 0.5 percentage points higher, 0.5 percentage points lower, or with [–0.5,0.5] of the change in the national unemployment rate. The four equity dummies capture the amount of home equity at time $t-1$. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP $\times$ year fixed effects, and ν_i are individual fixed effects. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table C-7: Probability of Moving to Another CBSA. The Role of home value and Mortgage Size. Including ZIP × Year Fixed Effects

	(1)	(2)	(3)
Neg. shock × Home value	–1.94***	–2.31***	–2.26***
	(–14.56)	(–16.64)	(–16.39)
Neg. shock × Mortgage balance		1.69***	1.51***
		(12.98)	(11.64)
Neg. shock × Equity < 0%			0.57***
			(16.21)
Pos. shock × Home value	–1.73***	–1.77***	–1.83***
	(–13.24)	(–13.42)	(–13.85)
Pos. shock × Mortgage balance		1.26***	1.16***
		(9.55)	(8.90)
Pos. shock × Equity < 0%			0.46***
			(10.10)
ZIP × Year effects	Y	Y	Y
Individual effects	Y	Y	Y
No. obs.	9,384,908	9,353,077	9,353,077
No. clusters	5,629	5,629	5,629

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + +D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to CBSAs's unemployment rates. $D_{zt-1} \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects or state × year effects in column (3), and ν_i are individual fixed effects. A dummy for negative employment shock is included but not displayed. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10]% level.

Table C-8: Probability of moving to another CBSA.
Including Credit Scores/Excluding Individual-Level Fixed Effects

	(1)	(2)	Dropping Fixed Effects (3)
Neg. shock × Equity <= −20%	1.46***	1.37***	0.86***
	(23.82)	(18.69)	(20.59)
Neg. shock × Equity $(-20, 0]$%	0.52***	0.42***	0.41***
	(14.87)	(10.50)	(14.47)
Neg. shock × Equity >= 20%	–0.15***	–0.12***	–0.50***
	(–5.67)	(–3.77)	(–28.99)
Pos. shock × Equity <= −20%	1.05***	1.20***	0.47***
	(8.50)	(8.34)	(5.64)
Pos. shock × Equity $(-20, 0]$%	0.47***	0.43***	0.24***
	(10.57)	(7.96)	(8.16)
Pos. shock × Equity >= 20%	0.07**	0.06	–0.36***
	(2.09)	(1.62)	(–21.83)
Subprime score	0.26***	0.27***	–0.19***
	(9.29)	(7.91)	(–15.33)
Near prime score	0.11***	0.10***	–0.06***
	(4.75)	(4.00)	(–5.25)
Lagged change in equity		–1.64***	0.15
		(–9.58)	(1.47)
ZIP × year effects	Y	Y	Y
Individual effects	Y	Y	N
No. obs.	9,384,908	6,917,601	7,843,726
No. clusters	5,629	5,627	5,630

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1}\ (+\nu_i) + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment in a CBSA/state and the four equity dummies are variables for the amount of home equity at time $t-1$. See Section 3.3 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects or state × year effects in column (3), and ν_i are individual fixed effects. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table C-9: Probability of moving to another CBSA
CBSA × year fixed effects

	(1)	(2)
Neg. shock × Equity <= −20%	1.26***	1.26***
	(20.52)	(17.33)
Neg. shock × Equity $(-20, 0]$%	0.45***	0.38***
	(13.32)	(9.59)
Neg. shock × Equity $[0, 20)$%	excluded group	excluded group
Neg. shock × Equity >= 20%	–0.05*	–0.04
	(–1.74)	(–1.15)
Pos. shock × Equity <= −20%	0.78***	0.93***
	(7.00)	(7.08)
Pos. shock × Equity $(-20, 0]$%	0.40***	0.36***
	(8.97)	(6.75)
Pos. shock × Equity $[0, 20)$%	excluded group	excluded group
Pos. shock × Equity >= 20%	0.18***	0.16***
	(5.00)	(4.00)
Lagged change in equity		–0.32**
		(–2.08)
CBSA × year effects	Y	Y
Individual effects	Y	Y
No. obs.	9,384,919	6,917,607
No. clusters	5,631	5,629

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment in a CBSA/state and the four equity dummies are variables for the amount of home equity at time $t-1$. See Section 3.3 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ are (lagged) CBSA × year fixed effects or state × year effects in column (3), and ν_i are individual fixed effects. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table C-10: Moving CBSA.
CoreLogic-estimated current equity

	(1)	(2)
Neg. shock × Equity $\leq -20\%$	0.42***	0.38***
	(4.75)	(3.73)
Neg. shock × Equity $(-20, 0)\%$	0.05	0.06
	(0.69)	(0.65)
Neg. shock × Equity $[0, 20)\%$	excluded group	excluded group
Neg. shock × Equity $\geq 20\%$	0.21**	0.14
	(2.54)	(1.46)
Pos. shock × Equity $\leq -20\%$	0.24*	0.32**
	(1.72)	(1.96)
Pos. shock × Equity $[0, 20)\%$	–0.06	–0.08
	(–0.72)	(–0.77)
Pos. shock × Equity $(-20, 0)\%$	excluded group	excluded group
Pos. shock × Equity $\geq 20\%$	0.35***	0.29***
	(3.93)	(2.88)
Lagged change in equity		–0.02***
		(–5.07)
ZIP × year effects	Y	Y
Individual effects	N	N
No. obs.	1,087,091	780,733
No. clusters	5,334	5,293

Notes: The table shows estimated coefficients (and *t*-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment in a CBSA and the four equity dummies are variables for the amount of home equity at time $t-1$. See Section 3.3 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × year fixed effects. Sample: TU-LP, 2007–2009. Robust standard errors are clustered by ZIP code of residence at time $t-1$. *** (**) [*] significant at the 1 (5) [10] percent level.

D Supplementary Model Results

The remaining tables report results from simulated data and are intended to help explain the workings of the model better, and to demonstrate robustness to reasonable permutations of the regression specification and the calibration.

In order to better understand the mechanisms of the model, we tabulate instructive frequencies by equity categories for strong and weak regions in Table D-1. The first column shows the share of people, within the strong/weak regions, in each equity category. There are no big differences in the proportions of individuals in the equity categories, although a few more people have negative equity in the weak regions. Prices evolve similarly in both types of regions by construction, and the tabulation reveals that the evolution of house prices, rather than labor market conditions, is the main cause of underwater mortgages. The second column shows that unemployment rates do not differ much between the regions. The third column further helps to explain the model: the unemployed are significantly more likely to move and even more so if they are underwater, with the pattern being more pronounced for weak regions. The fourth column shows, for both strong and weak regions, that the propensity of employed people to move is clearly and monotonically declining in equity, as captured by our four categories.

Table D-2 displays correlations of the simulated variables when the equity dummies are interacted with dummies for weak and strong labor markets after the removal of fixed effects. Comparing these correlations with their empirical counterparts of Table C-2, the model matches the data in terms of the correlation of mobility with the lagged change in equity. The model displays a larger correlation of mobility with the interaction of strong regions with negative equity than in the data (comparing local strong to positive shock CBSAs).

Table D-3 shows correlations involving actual unemployment in weak and strong regions. Of note is the strong correlation of foreclosure with mobility and with negative equity for both employed and unemployed individuals.

Table D-4 repeats the estimations of Table 6 allowing for region × year fixed effects. The coefficients to the lagged mortgage balance and equity are similar but the coefficient to the lagged home value is small and insignificant. This is an artifact of the way the model is constructed, because most of the variation in home values is by construction at the region × year level.

From (model) Table 7, unemployment plays a major role in mobility and the higher mobility of individuals with very negative equity in weak markets is likely a reflection of that. In Table D-5, we return to the detailed equity categories and compare the moving propensities of employed versus unemployed workers, using predicted equity. We include region × year fixed effect here in order to compare to (empirical) Table 2. All coefficients are relative to employed consumers with low positive equity.[46] From column (1), unemployed individuals in strong regions are much more likely to move than employed individuals, and this holds even more strongly in weak regions, see column (3), where a smaller fraction of job offers are local. Employed individuals with low equity are more likely to move than employed individuals with high equity. A positive equity shock reduces the probability of moving, but including these has little effect on the mobility impact of being underwater for the unemployed; however, the inclusion of the equity shock renders the effect of being underwater insignificant for the employed, indicating that the equity shock is more correlated with the underwater dummies for this group. Overall, employment status is a strong predictor of mobility, but its impact is about twice as high for those with negative equity.

Table D-6 explores whether our results are dependent on the subprime-sample approximation used in Table 5, with overweight of low-equity individuals to match the empirical sample scheme of Table 2. It turns out that the propensity to move for people with low equity is still higher and significant in most cases, but the coefficients are smaller than in Table 5. In an unreported regression, we dropped the region $\times$ year fixed effect, and the effects were more similar to those found using the "subprime" sample.[47] We believe that this pattern occurs because the sample now has less variation, with 75.83 percent of the observations in the highest equity category, but we do not explore this further. Because actual equity is determined by individual-specific shocks to a much larger extent, the variation in the region-year demeaned terms is larger, and the results for this simulated sample are very similar to the "subprime" sample. In either event, there is no lock-in.

We examine the effect of dropping individuals after they move, which we do in order to match the empirical sampling. Table D-7 reports results from a sample where movers remain in the sample. From comparison with the previous table, it is clear that this does not affect the results.

The following tables report results, using the same regression specification as Table 5, but changing the model itself. The main point of these tables is to show that the relationship between equity and mobility is robust to reasonable changes in model assumptions.

Table D-8 examines how the results change if unemployed individuals who move suffer a bigger loss of matching capital; that is, if moving entails a larger loss of permanent income (now 3 percent compared with the benchmark 1 percent). The results do not change much.

Table D-9 makes the gain of moving larger for the employed. The effect of this is to make the moving propensity of negative-equity individuals higher in strong regions than in weak regions. This is not surprising, but nothing much changes otherwise.

Table D-10 adjusts the probabilities of receiving external offers such that they are the

[46]There are seven identified equity-employment status interaction dummies in these regressions because we use individual-level unemployment status instead of region-level unemployment rates.

[47]Without regional dummies, the dummy variables are orthogonal to each other and the results do not change by having more individuals in other categories.

same for employed and unemployed workers, by lowering the probability of outside offers for the unemployed in the strong region and increasing the probability of outside offers for the employed in the weak region.[48] The main impact is to increase the tendency of low-equity individuals to move from weak regions.

Table D-11 limits the gains/losses from moving to the transitory income component and keeps the permanent income component the same as in the home region. In this specification, the unemployed have to accept a negative transitory shock when accepting an out-of-region job offer while the out-of-region job offers considered by the employed entail a positive transitory shock. In this setup, negative-equity unemployed consumers are still more likely to move than those with positive equity, although the coefficients become smaller when the shock to equity is included.

Table D-12 shows that the results change little if the moving costs are lowered. The benefit of getting a job dominates moving costs, and making them lower does not affect our results (which do not depend on the number of people moving, but on the relative tendencies to move between people in different equity categories).

[48]The parameters labelled a_2 and b_2 in the model are now 5 percent in both types of regions.

Table D-1: Frequencies by Equity Category in the Model.
(Owners with positive mortgage balance, aged 25–60)

	Equity % in category (1)	Unemployed % in category (2)	% Moving Unemployed (3)	% Moving Employed (4)	% Moving All (5)
Weak Region, Actual Equity					
Equity $\leq -20\%$	1.6	9.9	21.6	4.9	6.6
Equity $(-20, 0)\%$	13.1	7.1	19.9	2.5	3.7
Equity $[0, 20)\%$	11.8	8.3	16.5	0.7	2.0
Equity $\geq 20\%$	73.6	4.4	19.0	0.4	1.2
Weak Region, Predicted Equity					
Equity $\leq -20\%$	2.8	7.7	23.3	1.7	3.4
Equity $(-20, 0)\%$	13.3	6.3	19.2	1.9	3.0
Equity $[0, 20)\%$	19.3	5.2	19.9	0.8	1.8
Equity $\geq 20\%$	64.6	5.0	18.0	0.4	1.3
Strong Region, Actual Equity					
Equity $\leq -20\%$	1.5	10.0	9.9	4.8	5.3
Equity $(-20, 0)\%$	12.8	6.9	9.6	2.5	3.0
Equity $[0, 20)\%$	11.5	6.9	6.0	0.7	1.1
Equity $\geq 20\%$	74.3	4.7	9.2	0.3	0.7
Strong Region, Predicted Equity					
Equity $\leq -20\%$	2.9	7.8	11.2	1.7	2.4
Equity $(-20, 0)\%$	13.2	6.1	8.3	1.9	2.3
Equity $[0, 20)\%$	19.6	5.2	8.5	0.8	1.2
Equity $\geq 20\%$	64.3	5.1	8.8	0.4	0.8

Notes: Local weak regions and local strong regions differ in the intensity of local versus non-local job offers (80% and 90%, respectively). We pool data from all individuals and all four periods of the simulated data used in the regressions reported in Table 5. Employment status and equity categories are defined year-by-year, so individuals may move between these categories.

Table D-2: Model Data: Correlation Matrix for Aggregate Regressions. Region × Year and Individual Fixed Effects Removed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Moved non-locally	1									
(2) Local Weak × Equity $\leq -20\%$	0.020	1								
(3) Local Weak × Equity $(-20, 0)\%$	0.035	–0.031	1							
(4) Local Weak × Equity $\geq 20\%$	–0.0054	–0.081	–0.18	1						
(5) Local Strong × Equity $\leq -20\%$	0.010	–0.014	–0.032	–0.083	1					
(6) Local Strong × Equity $(-20, 0)\%$	0.020	–0.032	–0.071	–0.18	–0.032	1				
(7) Local Strong × Equity $\geq 20\%$	–0.035	–0.082	–0.18	–0.48	–0.084	–0.18	1			
(8) Lagged change in equity	–0.037	–0.29	–0.41	0.27	–0.29	–0.41	0.28	1		
(9) Lagged actual equity	–0.070	–0.12	–0.34	0.29	–0.11	–0.34	0.30	0.47	1	
(10) Lagged equity	–0.047	–0.19	–0.35	0.42	–0.20	–0.35	0.41	0.60	0.63	1

Notes: The table shows correlation coefficients for the variables used in the regression analysis with simulated data. "Moved non-locally" is a dummy variable that equals 100 if an individual moved to another region since the previous year. "Local Weak" ("Local Strong") is a dummy variable that equals one if the frequency of local to non-local job offers for the unemployed is 80–20 (90–10). The frequency of non-local offers for the employed is the same across regions, 5 percent. These dummy variables are interacted with the dummies corresponding to the amount of *predicted equity* an individual has in the period when the moving decision is made. Equity refers to predicted equity unless otherwise indicated.

Table D-3: Correlation Matrix for Individual Regressions. Region × Year and Individual Fixed Effects Removed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong Regions										
(1) Moved non-locally	1									
(2) Unemployed × Equity $\leq -20\%$	0.066	1								
(3) Unemployed × Equity $(-20, 0)\%$	0.066	0.00062	1							
(4) Unemployed × Equity $> 20\%$	0.061	–0.013	–0.030	1						
(5) Employed × Equity $\leq -20\%$	0.011	–0.012	–0.0083	–0.070	1					
(6) Employed × Equity $(-20, 0)\%$	0.00045	–0.0021	0.054	–0.095	–0.046	1				
(7) Employed × Equity $\geq 20\%$	–0.060	–0.0021	–0.064	–0.091	0.012	–0.23	1			
(8) Lagged change in equity	–0.033	–0.12	–0.17	0.044	–0.43	–0.57	0.40	1		
(9) Foreclosed dummy	0.15	0.085	0.14	–0.030	0.11	0.32	–0.088	–0.34	1	
(10) Unemployed dummy	0.15	0.20	0.27	0.47	–0.043	–0.058	–0.45	–0.019	0.045	1
Weak Regions										
(1) Moved non-locally	1									
(2) Unemployed × Equity $\leq -20\%$	0.097	1								
(3) Unemployed × Equity $(-20, 0)\%$	0.13	0.00080	1							
(4) Unemployed × Equity $> 20\%$	0.097	–0.020	–0.040	1						
(5) Employed × Equity $\leq -20\%$	0.0044	–0.010	–0.0095	–0.061	1					
(6) Employed × Equity $(-20, 0)\%$	–0.017	–0.0019	0.050	–0.096	–0.040	1				
(7) Employed × Equity $\geq 20\%$	–0.090	–0.0031	–0.071	–0.081	0.011	–0.24	1			
(8) Lagged change in equity	–0.033	–0.11	–0.17	0.041	–0.42	–0.58	0.42	1		
(9) Foreclosed dummy	0.16	0.091	0.13	–0.021	0.11	0.31	–0.096	–0.34	1	
(10) Unemployed dummy	0.25	0.20	0.29	0.46	–0.040	–0.063	–0.44	–0.025	0.062	1

Notes: The table shows correlation coefficients for the variables used in the regression analysis with simulated data. "Moved non-locally" is a dummy variable that equals 100 if an individual moved to another region since the previous year. "Unemployed" ("Employed") is a dummy variable that equals one if the individual is unemployed (employed) the period when the moving decision is made. These dummy variables are interacted with the dummies corresponding to the amount of *predicted equity* an individual has in the period when the moving decision is made. Equity refers to predicted equity unless otherwise indicated.

Table D-4: Model. The Role of Variables with Empirical Counterparts: Home Value and Mortgage Size. Including Region × Year Fixed Effects

	Actual House Val./ Equity			Predicted
	(1)	(2)	(3)	(4)
Local Weak × Home value	–2.87**	–2.82**	0.00	–0.83
	(–2.63)	(–2.57)	(0.00)	(–0.75)
Local Weak × Mortgage balance		0.14***	0.09*	0.15***
		(2.97)	(1.80)	(3.13)
Local Weak × Equity< 0			3.23***	1.12***
			(9.72)	(4.56)
Local Strong × Home value	–2.49***	–2.48***	–0.13	–0.87
	(–2.98)	(–2.98)	(–0.18)	(–1.04)
Local Strong × Mortgage balance		0.02	–0.02	0.03
		(0.63)	(–0.65)	(0.83)
Local Strong × Equity< 0			2.98***	1.03***
			(8.38)	(5.15)
Region × Year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs	190,129	190,129	190,129	190,129
No. clusters	54	54	54	54

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{t-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column of the table. $D_{t-1} \times \mu_{t-1}$ and ν_i are region × time fixed effects and individual fixed effects. Home value and mortgage balance are log transformed.

Table D-5: Model. The Role of Employment Status (Predicted Equity)
(Owners with positive mortgage balance, aged 25–60)

	Strong Regions		Weak Regions	
	(1)	(2)	(5)	(6)
Unemployed × Equity $\leq -20\%$	11.07***	10.67***	20.27***	19.78***
	(4.22)	(4.09)	(6.02)	(5.90)
Unemployed × Equity $(-20, 0)\%$	8.54***	8.30***	19.59***	19.32***
	(4.58)	(4.50)	(7.49)	(7.41)
Unemployed × Equity $[0, 20)\%$	4.66***	4.66***	9.43***	9.41***
	(4.38)	(4.38)	(8.65)	(8.62)
Unemployed × Equity $\geq 20\%$	4.52***	4.71***	9.08***	9.31***
	(9.19)	(9.22)	(17.78)	(17.01)
Employed × Equity $\leq -20\%$	0.63**	0.23	0.63*	0.13
	(2.49)	(0.77)	(2.01)	(0.35)
Employed × Equity $(-20, 0)\%$	0.45**	0.24	0.39*	0.13
	(2.26)	(0.95)	(1.97)	(0.53)
Employed × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Employed × Equity $\geq 20\%$	–0.06	0.13	–0.12	0.11
	(–0.41)	(0.77)	(–0.63)	(0.55)
Lagged change in equity		–1.88*		–2.29*
		(–1.94)		(–1.97)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	95,510	95,510	94,511	94,511
No. clusters	27	27	27	27

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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. Results are for the Great Recession calibration described in Section 4.3.

Table D-6: Moving in the Model.
Not Matching the Distribution of Equity

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	0.24*	0.12	5.03***	5.03***
	(1.97)	(0.97)	(7.08)	(7.08)
Local Weak × Equity $(-20, 0)\%$	0.28***	0.23**	2.60***	2.59***
	(3.00)	(2.45)	(9.45)	(9.44)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.07	–0.02	–1.83***	–1.81***
	(–0.99)	(–0.23)	(–10.75)	(–10.48)
Local Strong × Equity $\leq -20\%$	0.16	0.05	4.36***	4.36***
	(1.64)	(0.46)	(6.15)	(6.15)
Local Strong × Equity $(-20, 0)\%$	0.24***	0.18**	2.37***	2.36***
	(3.10)	(2.30)	(8.48)	(8.47)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	–0.00	0.05	–0.67***	–0.65***
	(–0.04)	(1.00)	(–7.87)	(–7.32)
Lagged change in equity		–0.50***		–0.06
		(–3.19)		(–1.42)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	1,534,325	1,534,325	1,534,325	1,534,325
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5. The sample is different from that of Table 5 because here we do not adjust the sample to match the distribution of negative equity in the TU-LP data, where roughly 15 percent of the sample hold negative equity. In this sample, the distribution of predicted equity is as follows: (1) equity ≤ -20: 1.66%; (2) equity $(-20, 0)$: 4.95%; (3) equity $[0, 20)$: 17.86%; (4) equity ≥ 20: 75.83%. The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3

TABLE D-7: MOVING IN THE MODEL.
NOT DROPPING THOSE WHO MOVE NOR MATCHING THE DISTRIBUTION OF EQUITY

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	0.23*	0.07	5.10***	5.11***
	(1.89)	(0.52)	(7.10)	(7.10)
Local Weak × Equity $(-20, 0)\%$	0.25**	0.17*	2.62***	2.61***
	(2.54)	(1.79)	(8.94)	(8.94)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.08	–0.01	–1.89***	–1.87***
	(–1.14)	(–0.11)	(–10.79)	(–10.55)
Local Strong × Equity $\leq -20\%$	0.15	–0.01	4.41***	4.41***
	(1.51)	(–0.10)	(6.00)	(6.00)
Local Strong × Equity $(-20, 0)\%$	0.21**	0.13	2.38***	2.38***
	(2.65)	(1.61)	(7.78)	(7.77)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	0.01	0.08	–0.67***	–0.64***
	(0.11)	(1.40)	(–7.33)	(–6.83)
Lagged change in equity		–0.72***		–0.06
		(–3.77)		(–1.43)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	1,516,695	1,516,695	1,516,695	1,516,695
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5. The sample is different, because we do not attempt to match the distribution of negative equity in the TU-LP data (roughly 15 percent), nor do we drop consumers after their first move. In this sample, the distribution of predicted equity is as follows: (1) equity ≤ -20: 1.68% ; (2) equity $(-20, 0)$: 4.94%; (3) equity $[0, 20)$: 17.80%; (4) equity ≥ 20: 75.59% The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3.

Table D-8: Moving in the Model.
Higher Loss for the Unemployed, 3% vs. 1%

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	1.20***	0.63*	6.16***	6.16***
	(3.63)	(1.74)	(7.25)	(7.25)
Local Weak × Equity $(-20, 0)\%$	1.06***	0.76**	2.60***	2.60***
	(3.68)	(2.41)	(6.96)	(6.98)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.12	0.14	–0.68**	–0.68**
	(–0.60)	(0.63)	(–2.26)	(–2.24)
Local Strong × Equity $\leq -20\%$	1.23***	0.68	5.25***	5.25***
	(2.96)	(1.47)	(6.82)	(6.82)
Local Strong × Equity $(-20, 0)\%$	0.68***	0.39	2.39***	2.39***
	(2.79)	(1.52)	(7.76)	(7.79)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	0.07	0.33*	–0.15	–0.15
	(0.43)	(1.78)	(–0.70)	(–0.70)
Lagged change in equity		–2.57***		0.00
		(–3.27)		(0.03)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	188,808	188,808	188,808	188,808
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5 except that the unemployed experience higher income loss when moving non-locally for a job (3 percent vs. 1 percent). The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3.

Table D-9: Moving in the Model.
Higher Gain for the Employed, 3% vs. 1%

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	1.08**	0.30	4.80***	4.78***
	(2.19)	(0.63)	(7.06)	(7.02)
Local Weak × Equity $(-20, 0)\%$	0.83***	0.40*	2.53***	2.55***
	(3.57)	(1.72)	(7.39)	(7.47)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.41	–0.04	–0.98***	–1.14***
	(–1.33)	(–0.13)	(–3.34)	(–3.62)
Local Strong × Equity $\leq -20\%$	1.39***	0.60	4.71***	4.69***
	(3.65)	(1.54)	(8.62)	(8.56)
Local Strong × Equity $(-20, 0)\%$	0.90***	0.48**	2.62***	2.65***
	(4.42)	(2.31)	(9.63)	(9.64)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	–0.10	0.27*	–0.12	–0.28
	(–0.67)	(1.80)	(–0.82)	(–1.61)
Lagged change in equity		–3.66***		0.36**
		(–5.42)		(2.53)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	188,961	188,961	188,961	188,961
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5 except that the employed receive a higher income increase when moving non-locally for a job (3 percent vs. 1 percent). The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3.

Table D-10: Moving in the Model.
Same probability of external offers for employed/unemployed

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	2.44***	1.48***	9.28***	9.27***
	(8.01)	(4.20)	(11.96)	(11.96)
Local Weak × Equity $(-20, 0)\%$	2.45***	1.95***	4.95***	4.97***
	(7.84)	(6.66)	(13.30)	(13.26)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	0.26	0.71***	–0.76**	–0.82***
	(1.33)	(3.38)	(–2.57)	(–2.79)
Local Strong × Equity $\leq -20\%$	0.76**	–0.20	4.76***	4.75***
	(2.38)	(–0.53)	(6.07)	(6.05)
Local Strong × Equity $(-20, 0)\%$	0.68***	0.19	2.14***	2.15***
	(3.70)	(0.97)	(6.82)	(6.86)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	–0.02	0.41**	0.31*	0.25
	(–0.12)	(2.17)	(1.91)	(1.42)
Lagged change in equity		–4.42***		0.15
		(–5.11)		(1.35)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	196,413	196,413	196,413	196,413
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5 except for the probabilities of job offers. In this case, the probability of a non-local job offer is the same for the employed and the unemployed, 5 percent in strong regions and 10 percent in weak regions. The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3.

Table D-11: Moving in the Model.
Only transitory gains/losses to Income from Non-Local Moves

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	1.41***	0.55	5.54***	5.53***
	(3.95)	(1.45)	(8.62)	(8.59)
Local Weak × Equity $(-20, 0)\%$	1.21***	0.76***	2.64***	2.65***
	(4.85)	(2.79)	(7.61)	(7.61)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.47**	–0.08	–0.95***	–1.01***
	(–2.13)	(–0.36)	(–3.01)	(–3.05)
Local Strong × Equity $\leq -20\%$	1.05***	0.20	5.31***	5.30***
	(3.82)	(0.69)	(7.92)	(7.90)
Local Strong × Equity $(-20, 0)\%$	0.87***	0.42*	2.53***	2.54***
	(3.86)	(1.70)	(7.98)	(8.04)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	0.00	0.40**	0.01	–0.04
	(0.02)	(2.44)	(0.07)	(–0.21)
Lagged change in equity		–3.95***		0.13
		(–5.45)		(1.00)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	189,183	189,183	189,183	189,183
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5 except that income gains/losses after accepting a non-local job offer are only transitory. Unemployed workers receive the lowest transitory shock when moving and employed workers receive the highest. The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3.

Table D-12: Moving in the Model.
Non-Local Employer Pays Half of the Moving Cost

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × Equity $\leq -20\%$	1.47***	0.85**	6.06***	6.05***
	(4.80)	(2.52)	(8.69)	(8.65)
Local Weak × Equity $(-20, 0)\%$	0.95***	0.63**	2.71***	2.71***
	(3.65)	(2.24)	(8.38)	(8.39)
Local Weak × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Weak × Equity $\geq 20\%$	–0.05	0.24	–0.34	–0.38
	(–0.18)	(0.93)	(–1.12)	(–1.27)
Local Strong × Equity $\leq -20\%$	1.08***	0.46	5.11***	5.10***
	(3.22)	(1.29)	(7.71)	(7.70)
Local Strong × Equity $(-20, 0)\%$	0.95***	0.63***	2.24***	2.25***
	(4.49)	(2.89)	(7.18)	(7.21)
Local Strong × Equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group
Local Strong × Equity $\geq 20\%$	0.16	0.45**	–0.08	–0.13
	(0.80)	(2.17)	(–0.44)	(–0.60)
Lagged change in equity		–2.87***		0.09
		(–4.09)		(0.65)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	192,238	192,238	192,238	192,238
No. clusters	54	54	54	54

Notes: Model parameters as in Table 5 except that moving costs are 50 percent lower when accepting a non-local job offer (a government or employer subsidy). The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, and zero otherwise. X is a vector of (lagged) regressors listed in the first column, $D_{zt-1} \times \mu_{t-1}$ 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 the Great Recession calibration described in Section 4.3.

E Further Details on the Model

E.1 The household problem in recursive form

The consumer's optimization problem in its recursive formulation can be written as follows:

$$V(A,H,M,P,q,l,j) = \max\left\{V^{NF}(A,H,M,P,q,l,j), V^{F}(A,H,M,P,q,l,j)\right\},$$

where A, H, M, and P denote deposits, housing, mortgage, and permanent income, respectively; l denotes the employment state (employed or unemployed), q is the house-price state, which differs from the house price (q^* denotes the house price; the difference between q and q^* is discussed below), and j is age. NF and F denote "no foreclosure" and "foreclosure." Let C be nondurables, S housing services acquired in the rental market, o an indicator for homeownership, ζ_{j+1} the probability of being alive at age $j+1$, and ρ the discount factor. Let $U()$ and $B()$ be the utility function and the bequest function, respectively. The value function when there is no foreclosure can be written as follows:

$$\begin{aligned} V^{NF}(A,H,M,P,q,l,j) &= \mathbb{E}\Big[\max_{C',A',H',M',S'} \big\{U(C', o'H' + (1-o')S', j) \\ &+ \frac{1}{1+\rho}\sum_{q'} \pi(q'|q)\Big(\zeta_{j+1}V(A',H',M',P',q',l',j+1) \\ &+ (1-\zeta_{j+1})B(A',H',M',q')\Big)\big\}\Big], \end{aligned}$$

where houses are purchased at the beginning of the period (after income, labor and moving shocks have been realized) and render services the same period. Age changes at the end of the period. (The expectations operator is spelled out in equation E-1). The following constraints must be satisfied.

Non-negativity constraints:

$$C \geq 0;\ A \geq 0;\ M \geq 0; H \geq 0; S \geq 0.$$

Individuals cannot be owners and renters at the same time:

$$\begin{cases} H' = 0,\ S' > 0 & \text{if } o' = 0, \\ H' > 0,\ S' = 0 & \text{if } o' = 1. \end{cases}$$

Let I_m be a moving indicator (changing houses or receiving an exogenous moving shock, m_s):

$$I_m = \begin{cases} 0 & \text{if} \quad |H'/H - 1| \leq \xi \text{ and } \quad m_s' = 0, \\ 1 & \text{if} \quad |H'/H - 1| > \xi \text{ or } \quad m_s' = 1. \end{cases}$$

The budget constraint at age j can be written as:

$$\begin{aligned} & C' + r_s S' + A' + q^* H'(1 + \kappa I_m) - M' \\ & = (1 - \tau_y) W' + [1 + r_a(1 - \tau_y)]A - [1 + r_m(1 - \tau_y \tau_m)]M + (1 - \delta_h)(1 - \chi_j I_m) q^* H\ , \end{aligned}$$

where κ and χ_j represent buying and selling costs, respectively. The selling cost increases with age. Income is taxed at the rate τ_y and mortgage interest payments can be deducted at the rate τ_m.
There is a maximum LTV ratio for new mortgages but non-movers are not subject to margin calls:

$$\begin{cases} M' \leq (1 - \theta) q^* H' & \text{if} \quad I_m = 1, \\ M' < M & \text{if} \quad I_m = 0. \end{cases}$$

The value function when defaulting (only possible for owners) can be written as:

$$\begin{aligned} V^F(A, H, M, P, q, l, j) \quad &= \quad \mathbb{E}\Big[\max_{C', A', S'} \ \big\{ U(C', S', j) \\ &+ \quad \frac{1}{1 + \rho} \sum_{q'} \pi(q'|q) \Big(\zeta_{j+1} V(A', 0, 0, P', q', l', j + 1) \\ &+ \quad (1 - \zeta_{j+1}) B(A', 0, 0, q') \Big) \big\} \Big]. \end{aligned}$$

Owners who default on their mortgage must rent for a period.

The budget constraint becomes:

$$C' + r_s S' + A' = (1-\rho_W)(1-\tau_y)W' + (1-\rho_A)[1+r_a(1-\tau_y)]A - \rho_H(1-\delta_h)q^* H\ ,$$

where the penalties for default are the loss of any positive equity, payment of a percentage ρ_W of current income, and payment of a small percentages ρ_H and ρ_A of the home value and deposits, respectively. Individuals who default lose their home and their home equity (if any) but discharge all mortgage debt. The losses associated with foreclosure (in terms of assets) are included to produce a life-cycle profile of foreclosure that first increases with age and then decreases.

Income evolves as follows:

$$W' = \begin{cases} P'\nu\phi; \quad P' = P\gamma_j\epsilon\varsigma & \text{if } j \leq R \\ bP_R & \text{if } j > R, \end{cases}$$

where ν is an idiosyncratic transitory shock, ϕ is 1 for employed workers and less than one for unemployed workers, γ_j is a hump-shaped non-stochastic life-cycle component, ϵ is an idiosyncratic permanent shock, and ς is a factor that determines whether wages go up or down when moving to another location for a job.

Employment takes two possible states $l = \{e, u\}$, and there are three possible individual-specific employment outcomes for employed and for unemployed workers, which we index by l_s^e and l_s^u, respectively: if $l_s^e = 1$, the individual becomes unemployed, if $l_s^e = 2$, the individual receives a non-local offer, and if $l_s^e = 3$, the individual remains employed locally. For the unemployed: if $l_s^u = 1$, the individual receives a local offer, if $l_s^u = 2$, the individual receives a non-local offer, and if $l_s^u = 3$, the individual does not receive any offers. l evolves as follows:

$$
l' = \begin{cases}
\text{if } l = e & \begin{cases} u', & l_s^e = 1,\ p = a_1\,; \\ e', & l_s^e = 2,\ p = a_2;\ \text{non-local offer received; can take or not}\,; \\ e', & l_s^e = 3,\ p = 1 - a_1 - a_2\,; \end{cases} \\
\\
\text{if } l = u & \begin{cases} e', & l_s^u = 1,\ p = b_1\,; \\ \begin{cases} u', & l_s^u = 2,\ p = b_2\,;\text{non-local offer rejected}\,; \\ e', & l_s^u = 2,\ p = b_2\,;\text{non-local offer accepted}; \end{cases} \\ u', & l_s^u = 3,\ p = 1 - b_1 - b_2\,. \end{cases}
\end{cases}
$$

For a homeowner to accept a non-local offer, the owner must sell the home and become a renter for one period.[49]

The house-price state evolves according to a highly persistent AR(1) process:

$$q' = \rho_q q + \varrho.$$

The actual price paid is higher or lower by a certain percentage relative to the housing state (the shock, which has probability 0.5 of being positive or negative, is learned before decisions regarding C', S', H', A' are made):

$$q^* = q(1 + \mu); \quad \mu \in \{-.05, +.05\}.$$

E.2 Computational details

Because the utility function is homothetic, we can eliminate permanent income as a state variable by normalizing deposits, mortgages, housing, and consumption by permanent income and solving a normalized version of the

[49]In order to limit computational demands, we do not allow homeowners who receive a non-local offer to become renters and wait for a local offer at the same time. Employed homeowners receive non-local offers with increased permanent income prospects, so the imposed reduction in the choice set is unlikely to be binding for this group. Unemployed homeowners, on the other hand, receive non-local job offers that may entail lower income going forward. Unemployed homeowners who prefer to stay after receiving a non-local offer can do so if they stay in their current home or downsize to a smaller home instead of becoming renters (that is, equity extraction is still possible for this group).

household problem.[50] Holding deposits may be optimal for precautionary reasons: if house prices go down, it may not be possible to extract home equity without incurring transactions costs associated with selling the house. In sum, we have to keep track of six state variables.

Because of the non-convex adjustment costs, we cannot use techniques that rely on differentiability, and 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 transitory and permanent idiosyncratic income shocks, and three points for the house-price state (high prices, average prices, low prices). When choosing the grids for the key state variables (deposits, housing, and mortgages), 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. Grids are denser for these three state variables around the neighborhoods where a significant fraction of households are concentrated. Grids are for the normalized variables, so even a relatively small number of points would map into a large number of outcomes for the non-normalized variables. We use 15 grid points for housing and 35 for deposits and mortgages.

Evaluating the expectation term in the discretized version of the household problem entails performing the following summation over transitory and permanent income shocks, (ν, ϵ), (assumed to be i.i.d.); moving shocks, m_s (age dependent); i.i.d. houseprice shocks, μ; and employment shocks, l_s^l, (whose probabilities depend on the employment state, l).

$$\mathbb{E} = \frac{1}{N_\nu} \sum_{\nu} \frac{1}{N_\epsilon} \sum_{\epsilon} \sum_{N_{m_s}} \pi(m_s|j) \frac{1}{N_\mu} \sum_{\mu} \sum_{N_{l_s}} \pi(l_s^l|l) \ , \tag{E-1}$$

where l is one of the labor states (e, u) and j is age.

After normalizing by permanent income, P', the budget constraints for

[50] In a previous version of this paper with a different assumption on house prices (i.i.d. house-price growth), home prices could also be eliminated as a state variable with further normalization by house prices, which is not the case with an AR(1) process. Without house-price uncertainty, it is possible to eliminate one more state variable by combining deposits and mortgages into net financial assets, $A - M$—see Díaz and Luengo-Prado (2008) for details. With house-price uncertainty, this is not necessarily the case even if $r_m > r_a$.

those not defaulting and defaulting, respectively, become:

$$c' + r_s s' + a' + q(1+\mu)h'(1+\kappa I_m) - m' = (1-\tau_y)\nu\phi$$
$$+(\gamma_j \epsilon\, \varsigma)^{-1}\Big([1+r_a(1-\tau_y)]a - [1+r_m(1-\tau_y\tau_m)]m + (1-\delta_h)(1-\chi_j I_m)q(1+\mu)h\Big),$$

$$c' + r_s s' + a' = (1-\rho_W)(1-\tau_y)\nu\phi$$
$$+(\gamma_j \epsilon\, \varsigma)^{-1}\Big((1-\rho_A)[1+r_a(1-\tau_y)]a - \rho_H(1-\delta_h)q(1+\mu)h\Big),$$

where lower-case variables denote upper-case counterparts divided by permanent income.

The moving indicator can be rewritten in terms of normalized variables as follows:

$$I_m = \begin{cases} 0 & \text{if} \quad |(h'\gamma_j \epsilon\, \varsigma)/h - 1| \leq \xi \text{ and} \quad m_s = 0, \\ 1 & \text{if} \quad |(h'\gamma_j \epsilon\, \varsigma)/h - 1| > \xi \text{ or} \quad m_s = 1. \end{cases}$$

The margin of adjustment before paying adjustment costs is quite realistic and it is important when solving a discretized version of the model in order to avoid "false positives" for moving.

The collateral constraint becomes:

$$\begin{cases} m' \leq (1-\theta)q(1+\mu)h' & \text{if} \quad I_m = 1, \\ \gamma_j \epsilon\, \varsigma m' < m & \text{if} \quad I_m = 0. \end{cases}$$

Given our assumption on the utility function, the value function must be normalized by the factor $(\epsilon\gamma_j\varsigma)^{1-\sigma}$, where σ is the coefficient of relative risk aversion.

F Welfare Analysis

We examine the welfare implications of the model even if it suppresses many of the features of a full general equilibrium model. In particular, we ignore benefits to employers, endogeneity of local wages, and potential costs to workers who may be crowded out. However, we can evaluate the order of magnitude of the benefits of being able to move to other labor markets. We report on two simple experiments where we calculate the average utility across all individuals and periods for the last four years of our Great Recession calibration. We show the results of two alternative parameterizations of the model, keeping all (income, prices, etc.) shocks the same across parameterizations. Let B and A denote baseline and alternative, i individual, and t period. We compute average utility in the baseline case as:

$$\overline{u}^B = \frac{1}{T}\sum_t \frac{1}{N}\sum_i U(C_i^B, J_i^B),$$

where housing services are $J = o \times H + (1-o) \times S$, with o being a dummy for homeownership. We compute average utility for the alternative parameterizations of the model in the same fashion and compare $\overline{u}^B$ to $\overline{u}^A$.[51]

For our first experiment, we decrease non-local moving costs by 50 percent—which could be interpreted as a government subsidy aimed at improving geographical matching. We obtain an equivalent permanent increase in nondurable consumption (and utility) of 0.45 percent. For our second experiment, we assume that there is a zero probability of external offers and find an equivalent permanent reduction in nondurable consumption of 2.2 percent. Table F-1 reports gains/losses comparing young vs. old workers, and, unsurprisingly, the gain/loss decreases with age. Finally, we split individuals based on their equity positions at the peak of the boom under the baseline simulation into a low-equity group (less than 50 percent) and a high-equity group (50 percent or more)—where the 50 percent cut-off roughly corresponds to the median—and

[51] With a Cobb-Douglas utility function on nondurable and housing services and a coefficient of risk aversion of 2, utility ratios translate one-to-one into nondurable consumption ratios.

focus on homeowners with positive mortgage balances at the peak of the boom, aged 25–60, as in our regressions. We compare the utility of these individuals to that of individuals who receive exactly the same shocks as they receive but "live" in the alternative economies.

Lowering the non-local moving cost has a small impact, but shutting down out-of-region job offers leads to utility losses of 2.79 percent for the high-equity group and 3.24 percent for the low-equity group—the difference reflects the higher number of unemployed in the low-equity group, but we do not explore this issue further.

Table F-1: Welfare Comparisons.
Gain/Loss, Nondurable Consumption (%)

Group	1/2 cost of non-local moves (1)	No non-local offers (2)
All	0.45	–2.18
Age 25–44	0.70	–2.68
Age 45–60	0.32	–2.10
Low Equity	0.08	–3.24
High Equity	0.02	–2.79

Notes: The table reports the equivalent increase/decrease in nondurable consumption when moving from our baseline calibration to the alternative calibration described by the column heading. Gains/losses are calculated over the Great Recession simulation period of our regressions, four periods with house-price states {high,high,low,low}. The age split is based on an individual's age at the peak of the boom. Low (High) Equity means equity of less (more) than 50 percent at the peak of the boom period in the baseline simulation, and the grouping excludes individuals who are renters or own their house outright.