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

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Abstract:
Using individual-level credit reports merged with loan-level mortgage data, we estimate how mobility relates to home equity when labor markets are weak or strong. We control for constant individual-specific traits with fixed effects and find that homeowners with negative home equity move to other metropolitan areas more than other homeowners. We use a dynamic quantitative model of consumption, housing, employment, and mobility to interpret our findings. The model illustrates that the gain from accepting a job in another area outweighs the cost of disposing of underwater property and replicates the data well.

JEL Classifications: E21, J61, R23

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1 Introduction

The severe decline in house prices during and after the Great Recession, which started in late 2007, may have hampered adjustment in U.S. labor markets by limiting mobility of unemployed workers. Mobility will suffer if unemployed workers are reluctant to leave homes that, with debt exceeding value, cannot be disposed of without injecting cash or defaulting—a pattern referred to as "housing lock-in." If such reluctance keeps workers from moving from depressed areas to areas with available jobs, the Beveridge curve, which depicts the relationship between vacancies and joblessness, may shift outward. For example, the *Economist* of August 28, 2010, tells this story in an article predicting higher unemployment in the United States (page 68, and leader, page 11). However, strong evidence has been hard to come by.

Using credit report data, we provide evidence that labor market adjustment in the United States is not significantly hampered by the inability of households with negative home equity to move to better job prospects and, using a theoretical model, we demonstrate that our estimates are plausible. Empirically, the amount of individual-level home equity correlates negatively with mobility, contradicting the *Economist*'s story. Using simulated data from a model that allows for households to choose nondurable consumption and housing consumption, subject to realistic costs of buying and selling houses, we are able to replicate the patterns in the data. In the model, the unemployed are more likely to move; however, low home equity predicts higher mobility regardless of employment status. This pattern is stronger in regions with relatively weaker local employment prospects, which matches up well with the empirical results. Analyzing the quantitative predictions of the model, we find that low-equity individuals, whether employed or not, are more likely than others to accept out-of-region job offers, because the utility gain from increased income is higher when equity is low.

We are able to 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 combined dataset is called Consumer Risk Indicators for Residential Mortgage-Backed Securities, for which we will use the label "TU-LP." The TU portion of this dataset contains credit information for borrowers with non-agency securitized mortgages.[1] The LP portion of this dataset has information on loan and borrower characteristics for about 90 percent of all non-agency securitized mortgage loans (in the following, we use the terms "mortgage" and "loan" interchangeably for the more cumbersome term "mortgage loan"). For each mortgage, we observe credit scores, debt-to-income ratios, loan-to-value (LTV) ratios at the time of loan origination, the location of the property (ZIP code), its monthly performance after securitization, and an extensive list of loan characteristics, but no credit information after origination. Data for credit after origination are available in the TU portion of the data. We use this combined dataset because both mortgage-level and borrower-level attributes are available for each mortgage. Importantly, we observe directly the value of the house and the size of the primary loan at origination, and we then predict home equity, assuming the value of the house varies with the average price level in the ZIP code where the property is located.

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 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

[1] 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.

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 that used in prior studies 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; 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 not unambiguous either. 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.[2] This lock-in effect is almost entirely due to a reduction 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

[2]The American Community Survey does not publish individual-level data, so only averages across individuals can be observed.

another county or state did not depend on 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.[3] 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 MSA-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 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 (DSGE) 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

[3]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).

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 agents with high versus low home equity; it is not informative about aggregate mobility or about agents' 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.[4]

3 Data, Regression Specification, and Results

3.1 Data

We focus on the period of the Great Recession and use the years 2006–2009 so that moving rates are defined for 2007–2009. The TU-LP dataset contains about 300 credit characteristics for anonymized consumers who had at least one non-agency securitized mortgage at any point during 2007–2009. As mentioned earlier, the dataset was created by TransUnion who merged credit report data with mortgage information from LP.[5] In the TU portion of the

[4]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.

[5]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

data, we observe at the individual level what kind of debt and how many accounts consumers had, and how they managed payments on their accounts. We also have, for each consumer, monthly credit scores and up-to-date mailing ZIP codes, which allows us to determine if an individual moves.

The LP portion of the dataset contains information about mortgages at origination and after securitization for over 90 percent of all U.S. non-agency securitized mortgages, totalling about 20 million subprime and Alt-A loans and 4.4 million prime loans. For each mortgage in the LP dataset, we observe the borrower's credit score, owner occupancy status at origination, and LTV ratios at mortgage origination. In addition, we know the ZIP code for the property location, which is not necessarily the same as an individual's mailing address. Property ZIP codes allow us to merge individual-level data with macro data on house prices and employment in the areas where people live. A weakness of our data is that we do not have demographic, income, or non-housing wealth information. The dataset is not representative of the U.S. population, but subprime borrowers, who are over-represented, are particularly likely to have negative home equity.

The main cleaning restrictions applied to the data are the following: (1) we drop observations for which an individual's property ZIP code differs from the mailing (residence) ZIP code at time $t-1$, when the individual's moving decision is made. A discrepancy may indicate either an error, that the owner receives mail elsewhere or, more importantly, that the property is not owner-occupied. (2) We drop observations if the balance-to-limit ratio on all mortgages is either zero or missing, in order to eliminate 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, for whom considerations of mortgage debt are no longer present when they decide to relocate. (3) We further drop individuals who default on their mortgage despite having more

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).

than 20 percent equity in their homes. This eliminates a few individuals for whom measurement error in equity is likely to be substantial.[6] (4) Finally, we randomly select 50 percent of the borrowers in order to obtain a dataset that is more manageable in terms of processing time when we perform regressions.

Most of the mortgages in our sample are classified as subprime or Alt-A.[7] 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 non-existent in the prime market). These hybrid mortgages were short-lived, with 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. We display the geographical distribution of negative equity in Figure 1, from which it can be seen that negative equity by 2007 was prevalent in Michigan and by 2009 in many other states, including Arizona, Florida, Nevada, and West Virginia.

In the combined TU-LP dataset, if a person had a mortgage terminated at time t and moved to some other location at time $t+1$ and did not secure another LP loan at time $t+1$ (the majority of cases), we do not have infor-

[6] "Default" refers to default on mortgages only. If the consumer defaults, the lender forecloses and "default" and "foreclosure" refer to the same event.

[7] 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.

mation on that individual's homeownership status and home equity at time $t+1$. Therefore, as we normally do not observe multiple moves for each individual, for a clean sample selection our regressions are performed on a sample where individuals are dropped after the first move. (We similarly drop households after they move, when using simulated data, in order to have households selected according to the same criteria.)

We augment loan-level data with characteristics for the corresponding ZIP codes, Core Based Statistical Areas (CBSAs), and states.[8] We use the U.S. ZIP Code Database to match CBSAs/states and ZIP codes.[9] CBSA-level and state-level monthly unemployment rates and employment levels are obtained from the Bureau of Labor Statistics.[10] ZIP code-level house-price indices (HPI) are obtained from CoreLogic. These indices are calculated using a weighted repeat sales methodology, and they are normalized by setting the index value to 100 for January 2000.

3.2 Variable definitions

We construct dummy variables to capture shocks to households' employment possibilities in the area of their residence. Let Δu_{rt} denote the change in the annual unemployment rate in region r at time t, and Δu_t its average across all regions at time t. A shock to the unemployment rate in region r at time t is defined as $\text{Shock}^u_{rt} = \Delta u_{rt} - \Delta u_t$.

Based on the sign of Shock^u_{rt}, we create two dummy variables indicating whether the regional shock is positive or negative (that is, relatively weak local labor market conditions or relatively strong local labor market conditions). When the regional shock is positive, the dummy variable "Neg. shock" takes

[8] 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.

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

[10] 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.

the value of one, while the dummy variable “Pos. shock” equals one if Shock^u_{rt} takes a negative value. For examining robustness, we define similar dummy variables (with the signs properly adjusted) for changes in local employment and local vacancy rates (vacancy rates are based on help-wanted data from The Conference Board). We also show results for more categories, defined similarly, in our robustness section.

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

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

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

where we proxy the change in the value of an individual property since origination ($\text{Value}_{i,0}$) by the change in the house-price index at the ZIP code level between the origination period ($\text{ZIP HPI}_{i,0}$) and time t ($\text{ZIP HPI}_{i,t}$).

We create dummy variables that group homeowners into four categories based on the estimated amount of home equity: “Equity $\leq -20\%$” equals one if home equity is negative in an amount that exceeds 20 percent of the house value while “Equity $(-20, 0)\%$” equals one if home equity is negative, but numerically less than 20 percent of the house value. Similarly, the dummy variables “Equity $[0, 20\%)$” and “Equity $\geq 20\%$”equal one if home equity is positive but low (between 0 and 20 percent of the house value) or is above

20 percent of the house value, respectively. We use four equity categories for simpler interpretation, but in online Appendix A we show similar results using a higher number of categories. We interact each of the dummy variables for CBSA labor market shocks with the equity dummies. As a result, we obtain eight dummy variables. Table 1 summarizes the distribution of these dummy variables in the regression sample, along with other variables used: 1.71 percent of the individuals in our sample move CBSA in a given year, 5 percent of them have negative equity exceeding 20 percent of the house value, while another 11 percent are more moderately underwater.

We also control for credit scores, where 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.[11] We experimented with a "Foreclosure" dummy equal to one if a mortgage (from the LP data) is in foreclosure—a lender initiated the foreclosure process—or in REO (Real-Estate Owned), which means that a lender has taken over the property in year t. "Foreclosure" is, however, not very well defined in the data, obviously endogenous to equity, and we showed in a previous draft that its inclusion did not change our main conclusions, so this variable is not included in the empirical regressions.[12]For robustness, we test the lock-in hypothesis on several subsamples of our data. First, we show results for a subsample of mortgages excluding those associated with property purchased primarily for investment.[13] Second, most of the loans in the TU-LP dataset are either subprime or Alt-A, and about half of the loans are short-term hybrid mortgages, so we show results for a subsample that excludes both investment and

[11]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/`.

[12]During the Great Recession, people sometimes stayed in a house long after having stopped paying on the mortgage, or negotiated buy-outs, or followed other strategies that proliferated because banks were overwhelmed with bad payers. Foreclosure is also normally a direct result of having negative equity, so its inclusion would make the interpretation of the dummies less clear.

[13]LoanPerformance contains self-reported information about whether an individual's loan was taken out in order to invest in property other than his or her residence.

hybrid mortgages. We also show result for the subsamples prime, subprime, and Alt-A.

3.3 Moving rates

Table 2 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 Current Population Survey (CPS).[14] As shown in the top two panels of Table 2, 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.[15] In the bottom panel, we tabulate moving rates for homeowners using the CPS, which has much broader coverage than the credit bureaus; for example, it includes very young, highly mobile people who may not yet have a credit history, 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.

[14]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.

[15]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).

3.4 Regression specification and results

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

$$M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + \nu_i + u_{it}, \tag{2}$$

where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise. We focus on mobility between CBSAs because workers typically 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 fixed effects interacted with year dummies, which we refer to as "ZIP × year" fixed effects or dummies (we explore CBSA/state dummies interacted with year dummies in robustness tables), and ν_i are individual fixed effects. The index "z" is implicitly a function of "i," as it refers to the ZIP code z in which individual i resides at time $t-1$. X is a vector of (lagged) regressors, the most important of which are the interactions of home equity with labor market conditions for the area where consumer i resides.

We summarize this information in the form of the dummies for equity interacted with local labor market conditions as previously defined. We allow for four equity dummies because we prefer not to impose a linear relation and it gives us flexibility, while still keeping the number of parameters small. It is intuitive that individuals may be more likely to move from weak rather than strong regions, and although we do not model overall mobility, the relative impact on people with negative versus positive equity may be different between such regions.[16] Due to the presence of ZIP × year dummies, the interactions Neg. shock × equity $[0, 20)\%$ and Pos. shock × equity $[0, 20)\%$ are omitted in order to avoid perfect multicollinearity.[17]

[16] Ferreira, Gyourko, and Tracy (2010) use one dummy for negative equity in their smaller sample and they use a Probit model, but they do not allow for individual fixed effects. In the appendix, we examine whether our results are robust to using a higher number of equity and labor market shock categories.

[17] These dummies are not identified if CBSA-year dummies are included, and the ZIP-year dummies subsume these because the CBSA × year dummies are the sum over the ZIP codes

We further include the change in equity share and credit scores. A positive (say) shock to equity may affect mobility through various channels (for example, wealth shocks may change the consumer's tendency to tolerate more risk, inclusive of the risk related to relocation) besides affecting the consumer's equity position, so it is important to include this variable with the equity categories in order to sort out direct wealth effects from "underwater" effects. Individuals who have low credit scores may face lock-in because they have a hard time securing a mortgage. Low scores often go hand-in-hand with low equity, and the coefficient to the negative equity dummy may therefore be affected by omitted-variable bias if credit scores are not included in the regression. The number of other regressors is small because all constant individual-specific features are absorbed by the individual fixed effects, while ZIP code (and therefore also CBSA and U.S. aggregate) features and trends are absorbed by the ZIP $\times$ year dummies. Explanatory variables are lagged one year for the analysis to reflect credit or labor market conditions before the decision to move is made. We display robust standard errors clustered by ZIP code in the regressions.

We use a linear probability model because little is gained by adopting nonlinear models, such as probit and logit models, in panels with a short time dimension and a large number of individuals. Greene (2004), for example, 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 when allowing for both individual and ZIP $\times$ year fixed effects. Also, although the linear probability model is not a maximum-likelihood estimator, efficiency is not an important concern when the dataset is as large as ours.

Because of the 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.

in the CBSA of the ZIP $\times$ year dummies. Time dummies are also subsumed in the ZIP $\times$ year dummies.

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:

$$D_{it}^N P_{rt} - \frac{1}{T_i} \sum_{t=1}^{T_i} D_{it}^N P_{rt} = D_{it}^N - \frac{1}{T_i} \sum_{t=1}^{T_i} D_{it}^N \tag{3}$$

for the (majority of) cases where the MSA labor market dummy does not change and is set equal to one here in order to illustrate 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), the variation in the individual-specific equity dummy is caused 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.[18] We consider this assumption reasonable because individuals drop out of the sample the year after they move (and right-hand-

[18]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 below, 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.

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 the 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 × year fixed effects implies, in addition, that the equity regressor is also identified from its variation relative to its average value across the N_{zt} individuals in the ZIP code where an individual lives in a given year:

$$D_{it}^{N} P_{rt} - \frac{1}{N_{zt}} \sum_{i=1}^{N_{zt}} D_{it}^{N} P_{rt} = D_{it}^{N} - \frac{1}{N_{zt}} \sum_{i=1}^{N_{zt}} D_{it}^{N}, \tag{4}$$

where, again, we have assumed 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 we might spuriously assign differences between ZIP codes to equity effects on individual mobility.[19]

3.4.1 Results

Table 3 displays our main results, using unemployment shocks to measure local labor market conditions. As previously discussed, all regressions include ZIP × year and individual fixed effects. (We report the correlation matrix with fixed effects removed from each variable in online Appendix A). In all regressions

[19] 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.

with individual fixed effects, we deleted "singletons" (individuals who appear only in the regression dataset in one year).[20] The top eight regressors in Table 3 are our main variables of interest. The top four regressors are interactions of negative local labor market conditions with the equity dummies, while the next four regressors are interactions of positive local labor market conditions with the equity dummies. The omitted dummies identify people with low but positive equity, facing a negative and a positive regional shock, respectively.

It is immediately obvious that individuals with very negative equity are not geographically locked in; in fact, they are more likely to move than individuals with low positive equity. From the first column of Table 3, which considers CBSA moves 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 1.49 percent more likely to leave their CBSAs. More precisely, individuals with very negative equity positions are more likely to leave than individuals with low positive equity in the same ZIP code, in the same year, in CBSAs where CBSA unemployment increases relative to U.S. unemployment. Going forward, we will keep in mind that all comparisons are to individuals with low positive equity in the same ZIP code in the same year, without stating this explicitly. The 1.49 percent is a large effect compared with the 1.71 percent who move CBSA on average. In comparison, individuals with high positive equity are 0.23 percent less likely to move. In CBSAs with positive employment shocks, individuals with very negative equity are 1.23 percent more likely to leave their CBSAs, a lower effect, while those with high positive equity are 0.07 percent less likely to move. From the second column, individuals with subprime and, less strongly, near prime scores (with high statistical significance in both cases) are more mobile than individuals with prime scores. Because of the individual fixed effects, a more rigorous interpretation of the results is that individuals who have a subprime score but previously had a better score are more mobile than they were before, and vice versa. In the second column, we also include

[20]Singletons would not affect the results because the fixed effects would fit these observations perfectly, and the degrees of freedom would also be unaffected.

the (exogenous) lagged change in equity, in order to examine whether mobility depends on the size of equity shocks, per se, and not on whether the homeowner is underwater.[21] Conditional on the equity categories, a loss of equity results in higher mobility; however, the categories remain highly significant. The patterns are qualitatively similar for interstate moves, see column (3), although the estimated coefficients for all variables are lower for these moves. This is intuitive, as interstate moves generally 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 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 form of mortgage 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.[22] (However, given the large number of subprime borrowers, mobility of just this segment of population is of economic importance.) We report results from this sample in columns (4)–(6) and observe that the "no lock-in" result carries over to prime borrowers with very negative equity even more strongly. Individuals with very negative equity are 1.84 percent (2.39 percent) more likely to move out of CBSAs with negative (positive) labor market shocks than individuals with low positive home equity. The results are not statistically significant when more regressors are included (for interstate moves as well as CBSA moves), but the point estimates are very stable and similar to the results for the full sample. We therefore conclude that the patterns uncovered are not specific to subprime

[21]For brevity, we do not include a column with the lagged change in equity and no score categories, but the drop in precision of the estimates of the equity categories is, unsurprisingly, due to inclusion of the equity shock.

[22]Prime non-jumbo mortgages constitute a small fraction of our dataset, but there are still more than 40,000 observations in this subsample (after deleting singletons).

movers—a conclusion that will be reinforced in the following table.

Table 4 focuses solely on CBSA moves and includes the score categories and the lagged change in equity, as well as individual-level controls in all columns. Scanning the results, the general pattern regarding equity and mobility found in Table 3 holds up. The first column uses a sample of prime jumbo loans, and the results are very similar (to those of the second column of the previous table) 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 quite similar, although the change in equity is more important and the equity dummies somewhat less important. 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, except that the indicators for subprime and near-prime scores are insignificant because they hardly vary in this sample. In the column labeled "No invest.," we drop homes purchased for investment. The results are virtually unchanged from the corresponding column of Table 3, 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 5 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.[23] 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

[23]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.

positive equity, in CBSAs with positive labor market shocks, which likely is a statistical aberration.[24] In the second column, we use the number of vacancies in the CBSA to measure local labor market conditions. The results are similar to our baseline results as are the results in the third column, where employment growth in the CBSA, rather than unemployment, is used as the measure of local conditions. Appendix A contains more robustness results: regressions without individual fixed effects, with more equity categories, using an equity estimate reported by CoreLogic rather than predicted equity constructed by us, and including CBSA-year fixed effects instead of ZIP-year fixed effects.[25] Our findings are robust to such modifications.

Overall, the relationship between home equity and mobility is robustly estimated across different types of borrowers, across different types of states, and across different specifications. In view of this, and considering the very large number of observations used, we conclude that lock-in was not a feature of the Great Recession and that the benefits of moving, when possible, outweighed the costs of disposing of underwater mortgages. We next turn to formulating a model that will provide an interpretation of the empirical patterns found.

4 The Model

We examine whether the mobility patterns observed in the data can be explained by a model of forward-looking consumers who may lose their job, who choose whether or not to become homeowners, and who face reasonable costs of buying and selling real estate. Unemployed individuals obviously have an incentive to move to regions where jobs are available, but would a model, calibrated to data in a typical fashion, predict that this incentive would dominate the disincentive provided by the cost of buying and selling homes? Also, will low-equity movers choose to default on mortgages? We simulate our model and perform regressions on simulated data. If the results using model data

[24]Testing at a 5 percent level, one should find significance 5 percent of the time, even if there is no true relationship.

[25]A previously circulated version used CBSA-year fixed effects throughout.

match the results using empirical data, we conclude that the patterns in the data can be rationalized by our model, which implies roughly that nothing more than standard costs of moving, and typical gains from moving to a new job, are needed to explain why there is no lock-in from negative equity.

Our 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) foreclosure 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, housing equity above a required down payment can be used as collateral for loans, and foreclosure is allowed. There are no other forms of credit, tax treatment of owner-occupied housing is preferential as in the United States, and individuals face uninsurable earnings risk and uncertainty arising from house-price variation.

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 non-random 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 or owning a home (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 $U(C_t, J_t)$, where C is nondurable consumption and J is housing services. The expected lifetime utility in period 0 is $E_0 \sum_{t=0}^{T} (1+\rho)^{-t} \left[\zeta_t U(C_t, J_t) + (1-\zeta_t) B(X_t)\right]$, where $\rho \geq 0$ is the time discount rate, ζ_t is the probability of being alive at age t, X_t is the bequest, and $B()$ is 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 house value is paid when buying a house (interpreted as, for example, a tax or search costs). When selling a house, a homeowner loses a fraction χ of the house value (interpreted as, for example, fees to a real estate agent). The selling cost is 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 house value and deposits, respectively, at foreclosure.[26] 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 $\log \nu_t \sim N(-\sigma_\nu^2/2, \sigma_\nu^2)$. $\phi_t = 1$ 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, $\log \epsilon_t \sim N(-\sigma_\epsilon^2/2, \sigma_\epsilon^2)$, 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 requires selling their current home if they are homeowners). Employed workers who decline offers remain employed as do the remaining proportion $1 - a_1 - a_2$.

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

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.[27] 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, $W_t = bP_R$, $\forall t > R$.[28]

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 move one-to-one with local prices).[29] 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 deductible 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

[27] 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.

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

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

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).[30] 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 ($t = 61$). The retirement age is 65 ($t = 41$). Survival probabilities are taken from the U.S. Vital Statistics 2003 (for females), published by the National Center for Health Statistics. The implied fraction of working-age households is 75.6 percent.

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

$$U(C, J) = \frac{(C^{\alpha} J^{1-\alpha})^{1-\sigma}}{1-\sigma} \tag{5}$$

with curvature $\sigma = 2$.

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

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

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

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

are paid plus net financial assets: $X_t = q_t H_t(1 - \delta_h)(1 - \chi) + A_t - M_t$. 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).[31] 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 face different labor markets and house-price shocks, and we refer to each group as "a region." In our benchmark case, which we refer to as strong labor markets, 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 offer with 5 percent probability, becomes employed in the current location with 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 1 percent increase in permanent income ($\log \varsigma$) for an employed worker and a 1 percent decline for an

[31] 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.

unemployed individual—we consider different wage increases and declines associated with non-local job offers as well as different probabilities of the shocks, in Appendix A. 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).[32]

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 increases 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 shortcut 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

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

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 figures 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.[33] 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.[34] For the period 1989–2004, personal taxes represent 12.47 percent of personal income in the National Income and Product Accounts. As in Prescott (2004), this number is multiplied by 1.6 to reflect that marginal income tax rates are higher than average rates. The 1.6 number is the mean ratio of marginal income tax rates to average tax rates, based on TAXSIM (for details, see Feenberg 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

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

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

persistent autoregressive process of order 1, AR(1).

$$q_t = \rho_q q_{t-1} + \varrho_t. \tag{6}$$

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. $N(0, \sigma_\varrho)$, $\sigma_\varrho = 0.091$.[35] 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.

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.

[35]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 rental price is proportional to the house-price state. In particular,

$$r_{s,t} = q_t \, \frac{(1-\tau_y)r_a + \delta_h + \varepsilon}{(1-\tau_y)(1+(1-\tau_y)r_a)} \; . \tag{7}$$

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 6. Appendix B 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 home equity 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).[36] 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 house value to total wealth for homeowners over the life cycle. The average of these two ratios was a target of 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.

[36]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.

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, with 40,000 people each for a number of periods—recall that weak and strong regions differ in the proportion of local vs. non-local job offers households receive.[37] 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. 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 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.

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 the period after their first move, as we did for the empirical regression sample. We further 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 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 of ages 25–60.

Table 7 shows results from estimating regressions using the simulated data arranged to match the empirical regressions of Table 3 most closely; that is, using the simulated data arranged by region type (local weak or local strong) without relying on individual-level employment status. As in the empirical

[37] 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.

analysis, all regressions control for individual and region × year fixed effects. The results obtained using the model, see column (1), are very similar to the results using empirical data. For individuals with strongly negative equity, the propensity to move is 1.35 percent higher (than for the comparison group) in weak labor markets and 1.04 percent higher in strong labor markets. This is to be compared with the data results of 1.49 percent and 1.23 percent, respectively, shown in the first column of the empirical Table 3. We consider this a very good fit, and the fit is also quite tight for the other categories (low negative coefficients for very positive equity in both types of labor markets, for example). As in the data, a loss of home equity results in higher out-of-region mobility—see column (2) of Table 7, where the coefficient on strongly negative equity drops to 0.80 and 0.49 in weak and strong labor markets, respectively, compared with 0.59 and 0.55 in the data.

In columns (3) and (4), we consider simulated 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 one 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. Finally, in 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 signal that the consumer intends to default and move that no further explanatory power is left for the wealth shock.

We expect the benefit of moving to be particularly high for the unemployed and, in Table 8, we compare the moving propensities of employed versus unemployed workers, using predicted equity. This table does not have a match using the empirical data, where individual-level employment status is not observed, but serves to illustrate the model mechanism. All coefficients are relative to employed consumers with low positive equity.[38] We observe from column (1)

[38]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.

that unemployed individuals are much more likely to move than employed individuals, especially from weak regions where a smaller fraction of job offers are local. However, this is not the full story because mobility is relatively higher for individuals with low equity even if they are employed. This is somewhat surprising, so in column (2) we explore the role of equity shocks. Including these has little effect on the moving propensities of the unemployed, but it lowers the effect of the equity dummies for the employed so much that they are no longer significant. Our interpretation is that even if a worker is employed, if he or she has low equity, the raise associated with accepting an outside offer outweighs the cost of disposing of the house.[39]

In column (3), we include foreclosure rather than the equity shock as the additional regressor, which renders the coefficients for the unemployed slightly smaller. However, for the employed this has a larger effect and makes the coefficients on the negative equity categories negative. The interpretation is that employed individuals choose to default on their house and move if they receive an out-of-region offer—they do this in particular when they have very negative equity so that the foreclosure dummy usurps the significance of the very negative equity dummy. The dummy for low negative equity turns negative when foreclosure is included. The interpretation of this result is that many agents in this category default and move when receiving an offer but because the tendency to move is lower than in the very negative equity category, we obtain a negative coefficient.[40] Including both equity shocks and foreclosure, in column (4), makes the equity shock insignificant, indicating that most people who move due to a drop in wealth, do so via foreclosure. However, the causal relationship is that of column (2), which includes only the exogenous

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

[40]Another way of saying this is that the foreclosure coefficient is restricted to have the same effect on all categories, leaving the dummies to pick up any differential propensities to move.

shocks—the highly significant foreclosure variable has the different interpretation of pinning down the mechanism by which people react to the exogenous shock. Columns (5)–(8) show results for weak regions. Not surprisingly, mobility propensities of unemployed workers are much higher in those regions, while the mobility propensities of employed workers are similar to what they are in the strong regions.

Model Cross-Tabulations. In order to better understand the mechanisms of the model, we tabulate instructive frequencies by equity categories for strong and weak regions in Table 9. 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 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. Therefore, the pattern of overall mobility as a function of equity holdings applies to both employed and unemployed individuals, with negative-equity individuals being more likely to move. We conclude that a model calibrated in a standard fashion predicts that the benefit of accepting an out-of-region job offer will dominate the cost of moving for the unemployed. In utility terms, this mechanism is stronger for poorer households, which explains why we find the opposite of lock-in. *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 online Appendix C 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, and 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 low equity are more likely than other residents in their ZIP code to move to another labor market. We formulate, calibrate, and simulate a model with reasonable costs of moving, in order to interpret our findings. We find that the model, in which the economic benefits of accepting job offers outweigh the costs of moving, matches the estimated empirical patterns well. In summary, quantitative modeling predicts that the sharp decline in house prices observed in the United States in the Great Recession should not limit labor mobility, and empirical regressions on a very large dataset confirm this prediction.

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Table 1: Descriptive Statistics: Regression Sample

Variable	Mean	Std. Dev.
Moved CBSA	1.71	12.97
Equity $\leq -20\%$	0.05	0.22
Equity $(-20, 0)\%$	0.11	0.32
Equity $[0, 20)\%$	0.30	0.46
Equity $> 20\%$	0.53	0.50
Neg. shock (to local unemp. rate)	0.56	0.50
Neg. shock $\times$ Equity $\leq -20\%$	0.05	0.21
Pos. shock $\times$ Equity $\leq -20\%$	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 $[0, 20)\%$	0.16	0.37
Pos. shock $\times$ Equity $[0, 20)\%$	0.14	0.35
Neg. shock $\times$ Equity $\geq 20\%$	0.27	0.44
Pos. shock $\times$ Equity $\geq 20\%$	0.26	0.44
Subprime Score	0.20	0.40
Near prime score	0.13	0.33
Dummy for nonrecourse	0.43	0.50
Prime mortgage	0.21	0.41
Alt-A mortgage	0.34	0.48
Subprime mortgage	0.44	0.50
Investment purpose	0.03	0.17
Short-term hybrid	0.22	0.41

Notes: "Moved CBSA" is a dummy variable that equals 100 if an individual moved to another CBSA since the previous year. "Neg. shock (to local unemp. rate)" is a dummy variable that equals one if the difference between the annual change in the regional unemployment rate and the national average change is positive. "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. "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. 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 a house-price index from CoreLogic). "Investment purpose" is a dummy variable that equals one if a mortgage was originated primarily for investment purposes. "Short-term hybrid" is a dummy variable that equals one if a mortgage is 2/28 or 3/27 hybrid. These two variables are from CoreLogic. All listed variables except for moving rates have been lagged one year for the analysis.

Table 2: Moving Rates (percent)

Year	ZIP	CBSA	State
TransUnion, 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	MSA	State
2007	2.55	2.41	1.16
2008	2.07	1.95	0.96
2009	1.89	1.75	0.91
Overall	2.17	2.04	1.01

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 3: Probability of moving to another location

	All loans			Prime non-jumbo loans		
	CBSA (1)	CBSA (2)	State (3)	CBSA (4)	CBSA (5)	State (6)
Neg. shock × equity ≤ –20%	1.49***	0.70***	0.35***	1.84**	1.09	0.78
	(18.06)	(7.38)	(5.37)	(2.13)	(1.06)	(1.07)
Neg. shock × equity (–20, 0)%	0.45***	0.17***	0.12***	1.22***	0.96*	0.35
	(10.11)	(3.49)	(3.62)	(2.67)	(1.91)	(0.95)
Neg. shock × equity [0, 20)%	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock × equity ≥ 20%	–0.23***	–0.06	–0.07***	–0.10	0.07	–0.33
	(–6.48)	(–1.50)	(–2.61)	(–0.29)	(0.18)	(–1.10)
Pos. shock × equity ≤ –20%	1.23***	0.68***	0.44**	2.39	1.88	4.53
	(7.13)	(3.77)	(2.12)	(1.46)	(1.10)	(1.27)
Pos. shock × equity (–20, 0)%	0.54***	0.31***	0.21***	0.25	0.05	0.44
	(8.49)	(4.79)	(3.57)	(0.38)	(0.07)	(0.54)
Pos. shock × equity [0, 20)%	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Pos. shock × equity ≥ 20%	–0.07*	0.03	0.03	–0.78	–0.67	–0.14
	(–1.78)	(0.65)	(0.83)	(–1.61)	(–1.37)	(–0.29)
Subprime score		0.52***	0.24***		0.56	0.24
		(12.76)	(8.20)		(0.99)	(0.48)
Near prime score		0.21***	0.09***		–0.02	–0.06
		(6.65)	(3.52)		(–0.05)	(–0.13)
Lagged change in equity		–4.88***	–2.01***		–5.98	–3.70
		(–14.21)	(–8.66)		(–1.13)	(–0.93)
ZIP x year effects	Y	Y	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y	Y	Y
No. obs.	4068842	4068842	4046150	43360	43360	43114
No. clusters	5627	5627	5595	3346	3346	3326

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, and 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 3.2 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. 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 4: Probability of moving to another CBSA. Robustness I

	Prime jumbo	Subprime	Alt-A	Subprime score	No invest.	No invest. Nor hybrid
Neg. shock × equity $\leq -20\%$	0.76***	0.59***	0.68***	0.74***	0.68***	0.65***
	(2.94)	(4.51)	(4.38)	(3.22)	(7.03)	(5.95)
Neg. shock × equity $(-20, 0)\%$	0.34**	0.18**	0.10	0.21*	0.17***	0.20***
	(2.52)	(2.55)	(1.25)	(1.80)	(3.32)	(3.54)
Neg. shock × equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock × equity $\geq 20\%$	–0.16*	0.06	–0.12*	0.03	–0.06	–0.10**
	(–1.87)	(1.14)	(–1.70)	(0.41)	(–1.55)	(–2.32)
Pos. shock × equity $\leq -20\%$	1.42***	0.55**	0.68**	0.25	0.67***	0.67***
	(2.59)	(2.28)	(2.33)	(0.67)	(3.72)	(3.32)
Pos. shock × equity $(-20, 0)\%$	0.52**	0.31***	0.29**	0.33**	0.31***	0.30***
	(2.26)	(3.79)	(2.44)	(2.49)	(4.59)	(3.88)
Pos. shock × equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Pos. shock × equity $\geq 20\%$	–0.08	0.07	0.03	0.06	0.01	–0.02
	(–0.77)	(1.29)	(0.42)	(0.75)	(0.18)	(–0.45)
Subprime score	0.74***	0.44***	0.73***	0.03	0.51***	0.49***
	(3.39)	(9.74)	(8.43)	(0.33)	(12.42)	(10.17)
Near prime score	0.18	0.18***	0.18***	–0.09	0.22***	0.21***
	(1.08)	(4.86)	(2.84)	(–0.95)	(6.60)	(5.58)
Lagged change in equity	–3.76***	–6.21***	–4.89***	–6.14***	–5.12***	–4.57***
	(–4.74)	(–12.16)	(–8.20)	(–6.68)	(–14.13)	(–11.83)
ZIP × year effects	Y	Y	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y	Y	Y
No. obs.	934373	1726899	1399029	587909	3937783	3159571
No. clusters	5072	5618	5623	5544	5627	5627

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, and 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 "No invest" drops individuals who are identified by CoreLogic as buying property primarily for investment purposes. Column "No invest. nor Hybrid" further drops holders of "hybrid" loans (loans with an initial fixed rate which adjusts annually after the initial period). Column "Subprime" refers to individuals whose loans are labeled so by CoreLogic, while "Subprime score" refers to individuals with a VantageScore less than 641. Column "Alt-A" includes individuals who hold Alt-A loans, of which many are held by investors. "Prime" refers to individuals who hold prime loans, the majority of which are jumbo loans. 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 5: Probability of moving to another CBSA. Robustness II

	Non-recourse states	All states, vacancy rates	All states, empl. growth
Neg. shock × equity $\leq -20\%$	0.54***	0.68***	0.71***
	(4.33)	(6.51)	(6.61)
Neg. shock × equity $(-20, 0)\%$	0.14**	0.20***	0.16***
	(2.06)	(3.98)	(2.85)
Neg. shock × equity $[0, 20)\%$	excluded group	excluded group	excluded group
Neg. shock × equity $\geq 20\%$	–0.04	–0.09**	–0.03
	(–0.83)	(–2.38)	(–0.69)
Pos. shock × equity $\leq -20\%$	0.73**	0.61***	0.68***
	(2.49)	(3.88)	(5.49)
Pos. shock × equity $(-20, 0)\%$	0.34**	0.19***	0.27***
	(2.24)	(2.92)	(5.04)
Pos. shock × equity $[0, 20)\%$	excluded group	excluded group	excluded group
Pos. shock × equity $\geq 20\%$	0.20***	–0.03	–0.02
	(2.62)	(–0.59)	(–0.52)
Subprime score	0.71***	0.42***	0.52***
	(10.01)	(9.95)	(12.76)
Near prime score	0.31***	0.19***	0.21***
	(5.19)	(5.53)	(6.65)
Lagged change in equity	–4.86***	–4.31***	–4.94***
	(–10.02)	(–12.03)	(–14.53)
ZIP × year effects	Y	Y	Y
Individual effects	Y	Y	Y
No. obs.	1777160	3256562	4068842
No. clusters	1649	3973	5627

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, and 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 6: 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 (6) 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 7: Moving in the Model by Equity and Region Type.
(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
Adj. R sq.	0.508	0.508	0.513	0.513
No. obs.	190021	190021	190021	190021
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. 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 8: Moving in the Model. Individual Regressions with Predicted Equity.
(Owners with positive mortgage balance, aged 25–60)

	Strong Regions				Weak Regions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployed × equity ≤ −20%	11.07***	10.67***	9.05***	9.10***	20.27***	19.78***	17.65***	17.72***
	(4.22)	(4.09)	(3.62)	(3.66)	(6.02)	(5.90)	(5.26)	(5.31)
Unemployed × equity (−20, 0)%	8.54***	8.30***	6.50***	6.52***	19.59***	19.32***	17.40***	17.45***
	(4.58)	(4.50)	(3.75)	(3.80)	(7.49)	(7.41)	(6.81)	(6.83)
Unemployed × equity [0, 20)%	4.66***	4.66***	4.50***	4.50***	9.43***	9.41***	9.10***	9.10***
	(4.38)	(4.38)	(4.24)	(4.24)	(8.65)	(8.62)	(8.52)	(8.54)
Unemployed × equity ≥ 20%	4.52***	4.71***	4.34***	4.31***	9.08***	9.31***	8.77***	8.74***
	(9.19)	(9.22)	(8.84)	(8.74)	(17.78)	(17.01)	(17.09)	(16.18)
Employed × equity ≤ −20%	0.63**	0.23	–0.05	0.00	0.63*	0.13	–0.20	–0.12
	(2.49)	(0.77)	(–0.26)	(0.01)	(2.01)	(0.35)	(–0.76)	(–0.35)
Employed × equity (−20, 0)%	0.45**	0.24	–0.64***	–0.62**	0.39*	0.13	–0.85***	–0.80***
	(2.26)	(0.95)	(–3.16)	(–2.40)	(1.97)	(0.53)	(–4.19)	(–3.17)
Employed × equity [0, 20)%	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Employed × equity ≥ 20%	–0.06	0.13	–0.16	–0.18	–0.12	0.11	–0.23	–0.27
	(–0.41)	(0.77)	(–1.05)	(–1.18)	(–0.63)	(0.55)	(–1.17)	(–1.30)
Lagged change in equity		–1.88*		0.24		–2.29*		0.38
		(–1.94)		(0.31)		(–1.97)		(0.39)
Foreclosure			5.04***	5.05***			5.74***	5.75***
			(10.41)	(10.49)			(12.29)	(12.44)
Region × year effects	Y	Y		Y	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R sq.	0.509	0.509	0.519	0.519	0.548	0.548	0.557	0.557
No. obs.	95510	95510	95510	95510	94511	94511	94511	94511
No. clusters	27	27	27	27	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, 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 9: 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 Tables 7 and 8. Employment status and equity categories are defined year-by-year, so individuals may move between these categories.

Figure 1: Distribution of Negative Equity by State.

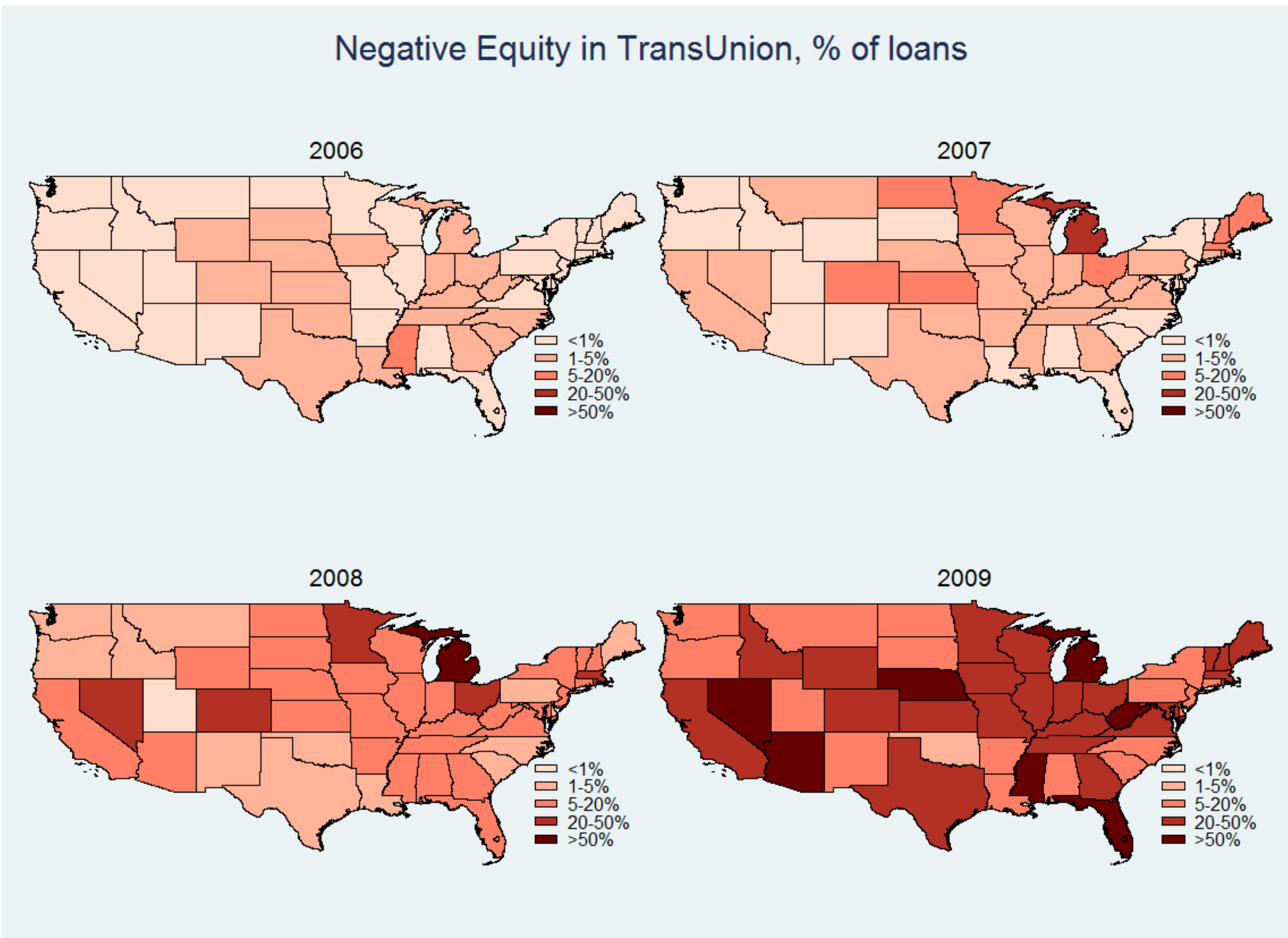
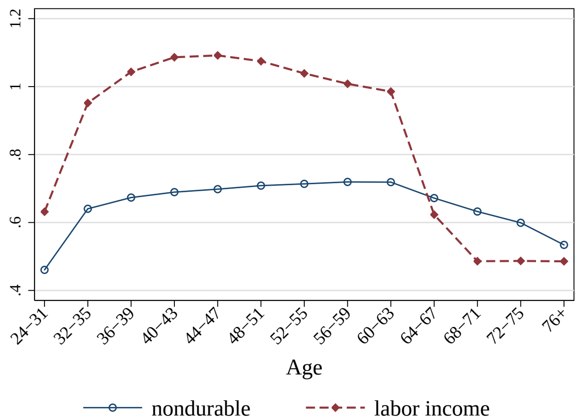


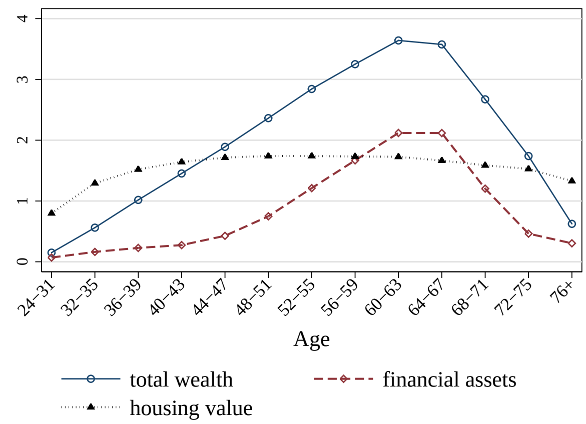
Figure 2: The Benchmark and the Data.

(Data on homeownership, wealth, and earnings come from the Survey of Consumer Finances, and are averages from 1989–2004. Data on moving rates are from Equifax, 1999–2008)

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

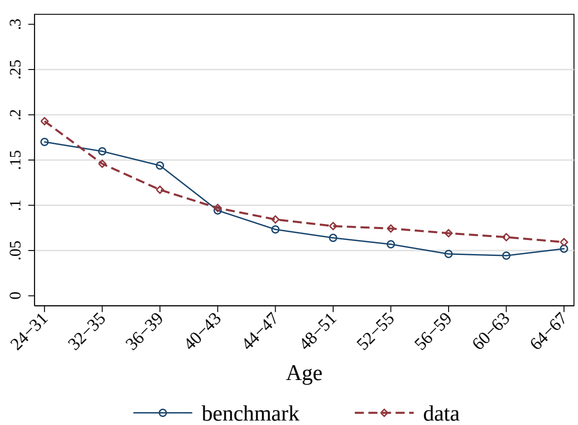


(a) Income and Consumption

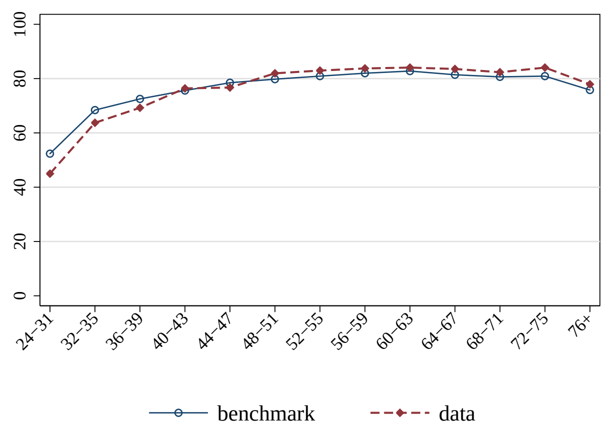


(b) Mean Wealth

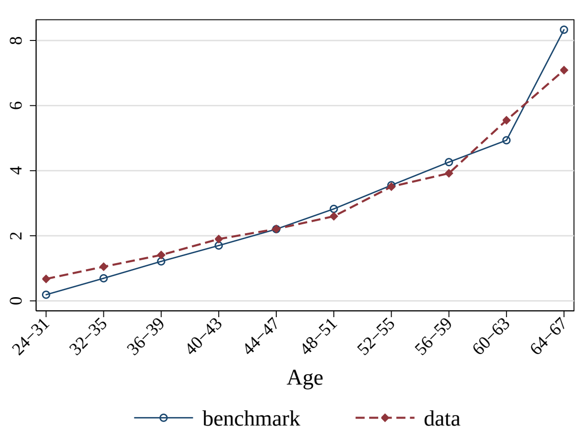
Match of Life-cycle profiles to the data



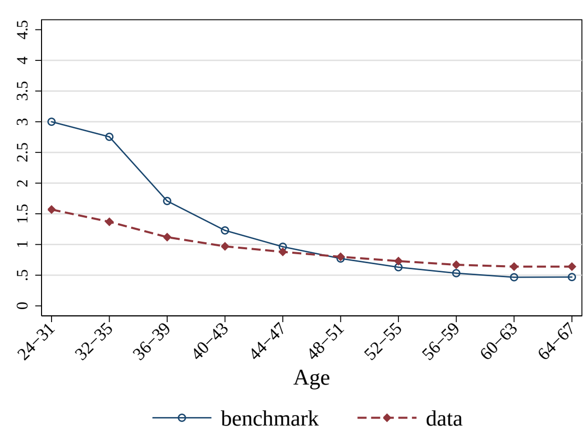
(c) Moving Rate



(d) Homeownership



(e) Median Wealth/Earnings Ratio



(f) Median Housing Value/Wealth Ratio

(Online Appendices)

A Supplementary Empirical and Model Results

In this appendix, we display several supplementary results—some using the empirical data to further establish the robustness of our empirical results, and some using the simulated data to help in explaining the model and to demonstrate that the model results are robust to alternative regression specifications and to alternative calibrations.

Table A-1 shows correlations for the variables in our regressions with individual and ZIP code $\times$ year fixed effects removed. The results tabulated in Table A-2 are from regressions similar to our main regressions in Table 3 but they include CBSA $\times$ year fixed effects instead of ZIP $\times$ year fixed effects. The results regarding equity levels are very similar to those reported in the main text, and the results regarding credit scores are almost unchanged, but the effect of a change in equity is much less significant when CBSA $\times$ year dummies are used. 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.

Table A-3 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 3, in which the regressions, properly, we argue, include individual fixed effects. The coefficient for individuals with very negative equity is smaller in strong labor markets without fixed effects, but still highly statistically significant. The effect of a change in equity is still negative and very significant, but the effect is smaller. The coefficients on “Subprime score” and “Near prime score” turn negative, even significantly so for the near-prime category. 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.

Table A-4 departs from the main regression of Table 3, but adding more equity categories. In weak labor markets, we find a monotonic decline in the propensity to move CBSAs with increasing equity. The pattern is not quite as monotone in strong labor markets, but it is still the case that negative equity correlates positively with mobility. The effect of scores and changes in equity are not much changed. We conclude that our results are not caused by having a small number of equity categories.

Table A-5 examines the case of three types of labor markets where "Rel. High Unemp." is a dummy taking the value 1 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 for the high and average unemployment-shock groups, but for the strongest labor markets, only the low negative equity group is significant and only when lagged equity is not included. There is no lock-in in any of the labor-market groups. The tendency for people not to move from strong labor markets is intuitive and is reflected in the regression 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.

In Table A-6, we repeat the main regression of Table 3 using current equity as reported by CoreLogic in their TrueLTV dataset.[41] Current equity is likely

[41] CoreLogic matched mortgages found in the LoanPerformance dataset to subsequent liens taken out on the same property. The resulting total mortgage indebtedness was combined

to be 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. The change in equity is not significant, which we believe is a signal of substantial measurement error.

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 regression specification and calibration.

Table A-7 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 A-1, the model matches the data exactly 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 A-8 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 A-9 gives more details on the effect of employment status interacted with actual equity on mobility in weak and strong regions and how the coefficients change when including lagged equity shocks and foreclosure. The results agree with those of Table 8—in particular, the result that employed individuals move in connection with foreclosure holds up.

Table A-10 explores whether our results are dependent on the subprime-sample approximation used for the regressions in Table 3. It turns out that the propensity to move for people with low equity is still higher and significant in

with CoreLogic's Automated Valuation Model (AVM) to estimate "true LTV."

most cases, but the coefficients are smaller than in Table 3. 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.[42] 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 CBSA-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.

Table A-11 examines the effect of dropping individuals after they move. 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 7, but changing the model itself. Table A-12 shows the results, for both estimated and actual equity, from simulations of a model where foreclosure is not allowed. In this model, agents would have to pay back any mortgage debt before they could move, which might be expected to generate lock-in. Compared with Table 8, the propensity to move of those with negative equity goes down, but only marginally, when estimated equity is used. So our main result is not dependent on the foreclosure option. Using actual equity, individuals with strongly negative equity move more, but the effect is no longer significant. This reflects the fact that the option of strategically defaulting has been taken away and agents would not gain by failing to maintain a house that they would have to sell rather than walk away from. Lagged changes in equity no longer predict mobility (conditional on the equity categories).

Table A-13 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 A-14 makes the gain of moving larger for the employed. The effect

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

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 A-15 adjusts the probabilities of receiving external offers such that they are the 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.[43] The main impact is to increase the tendency of low-equity individuals to move from weak regions.

Table A-16 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 A-17 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).

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

Table A-1: Correlation matrix. Regression sample ZIP code × Year and Individual Fixed Effects removed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Moved CBSA	1.000									
(2) Neg. shock × equity $\leq -20\%$	0.029	1.000								
(3) Neg. shock × equity $(-20, 0)\%$	0.013	–0.066	1.000							
(4) Neg. shock × equity $\geq 20\%$	0.015	0.034	–0.066	1.000						
(5) Pos. shock × equity $\leq -20\%$	–0.004	–0.038	–0.056	–0.046	1.000					
(6) Pos. shock × equity $(-20, 0)\%$	–0.014	–0.105	–0.110	–0.127	–0.004	1.000				
(7) Pos. shock × equity $\geq 20\%$	–0.017	–0.194	–0.177	–0.497	–0.046	–0.026	1.000			
(8) Subprime score	–0.002	0.087	0.064	–0.170	0.031	0.105	–0.103	1.000		
(9) Near prime score	–0.006	0.004	0.004	–0.091	0.005	0.041	–0.029	–0.218	1.000	
(10) Lagged change in equity	–0.037	–0.633	–0.337	0.044	–0.137	–0.047	0.426	–0.069	0.038	1.000

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 regional 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. "Subprime score" is a dummy variable that equals 1 if an individual has a credit score less than 661, and "Near prime score" is a dummy variable that equals 1 if an individual has a score between 661 and 700. "Lagged change in equity" is a change in predicted equity at time $t-1$.

Table A-2: Probability of moving to another location. CBSA/state × year fixed effects

	All loans		
	CBSA (1)	CBSA (2)	State (3)
Neg. shock × equity $\leq -20\%$	1.30***	1.05***	0.49***
	(15.60)	(11.31)	(8.03)
Neg. shock × equity $(-20, 0)\%$	0.38***	0.29***	0.17***
	(8.84)	(6.11)	(5.18)
Neg. shock × equity $[0, 20)\%$	excluded group	excluded group	excluded group
Neg. shock × equity $\geq 20\%$	–0.18***	–0.12***	–0.11***
	(–5.10)	(–3.26)	(–4.25)
Pos. shock × equity $\leq -20\%$	0.88***	0.67***	0.48**
	(5.49)	(4.04)	(2.56)
Pos. shock × equity $(-20, 0)\%$	0.46***	0.38***	0.28***
	(7.46)	(5.93)	(5.18)
Pos. shock × equity $[0, 20)\%$	excluded group	excluded group	excluded group
Pos. shock × equity $\geq 20\%$	–0.04	0.01	0.02
	(–0.91)	(0.16)	(0.49)
Subprime score		0.54***	0.25***
		(13.16)	(8.49)
Near prime score		0.23***	0.09***
		(7.06)	(3.87)
Lagged change in equity		–0.86***	0.18
		(–3.28)	(1.15)
CBSA × year effects	Y	Y	N
State × year effects	N	N	Y
Individual effects	Y	Y	Y
No. obs.	4068846	4068846	4046152
No. clusters	5629	5629	5596

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, and 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 3.2 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 A-3: Moving CBSA. No Individual Fixed Effects

	(1)	(2)
Neg. shock × equity $\leq -20\%$	1.14***	0.89***
	(20.91)	(15.24)
Neg. shock × equity $(-20, 0)\%$	0.56***	0.48***
	(15.50)	(13.01)
Neg. shock × equity $[0, 20)\%$	excluded group	excluded group
Neg. shock × equity $\geq 20\%$	–0.61***	–0.58***
	(–26.74)	(–25.14)
Pos. shock × equity $\leq -20\%$	0.59***	0.44***
	(5.41)	(3.91)
Pos. shock × equity $[0, 20)\%$	excluded group	excluded group
Pos. shock × equity $(-20, 0)\%$	0.35***	0.30***
	(8.40)	(7.05)
Pos. shock × equity $\geq 20\%$	–0.45***	–0.46***
	(–20.79)	(–21.15)
Subprime score		–0.03
		(–1.47)
Near prime score		–0.12***
		(–5.95)
Lagged change in equity		–2.16***
		(–7.43)
ZIP × year effects	Y	Y
Individual effects	N	N
No. obs.	5018129	5018129
No. clusters	5628	5628

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, zero otherwise, and 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 3.2 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × year fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t-1$. Sample: TU-LP, 2007–2009. *** (**) [*] significant at the 1 (5) [10] percent level.

Table A-4: Moving CBSA. More equity dummies

	(1)		(2)
Equity $< -50\%$ × Neg. shock	1.74*** (7.37)	Equity $< -50\%$ × Pos. shock	1.15 (1.56)
Equity $[-50, -40)\%$ × Neg. shock	1.14*** (6.01)	Equity $[-50, -40)\%$ × Pos. shock	0.63 (1.37)
Equity $[-40, -30)\%$ × Neg. shock	0.93*** (6.10)	Equity $[-40, -30)\%$ × Pos. shock	0.67** (2.24)
Equity $[-30, -20)\%$ × Neg. shock	0.66*** (5.92)	Equity $[-30, -20)\%$ × Pos. shock	0.94*** (4.76)
Equity $[-20, -10)\%$ × Neg. shock	0.35*** (4.29)	Equity $[-20, -10)\%$ × Pos. shock	0.52*** (4.31)
Equity $[-10, 0)\%$ × Neg. shock	0.17*** (2.84)	Equity $[-10, 0)\%$ × Pos. shock	0.33*** (4.60)
Equity $[0, 10)\%$ × Neg. shock	excluded group	Equity $[0, 10)\%$ × Pos. shock	excluded group
Equity $[10, 20)\%$ × Neg. shock	–0.13*** (–2.78)	Equity $[10, 20)\%$ × Pos. shock	–0.08 (–1.54)
Equity $[20, 30)\%$ × Neg. shock	–0.19*** (–3.21)	Equity $[20, 30)\%$ × Pos. shock	–0.13* (–1.94)
Equity $[30, 40)\%$ × Neg. shock	–0.18** (–2.28)	Equity $[30, 40)\%$ × Pos. shock	–0.07 (–0.87)
Equity $[40, 50)\%$ × Neg. shock	–0.16 (–1.59)	Equity $[40, 50)\%$ × Pos. shock	0.01 (0.08)
Equity $\geq 50\%$ × Neg. shock	–0.12 (–0.97)	Equity $\geq 50\%$ × Pos. shock	0.09 (0.70)
Subprime score	0.51*** (12.56)	Lagged change in equity	–3.46*** (–9.08)
Near prime score	0.21***	No. obs.	4,068,842
	(6.52)	No. clusters	5,627
		ZIP × year effects	Y
		Individual effects	Y

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_{zt-1} \times \mu_{t-1} + u_{it}$, 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. See Section 3.2 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ are (lagged) ZIP × year fixed effects. Robust standard errors are clustered by ZIP code of residence at time $t - 1$. *** (**) [*] significant at the 1 (5) [10] percent level.

Table A-5: Moving CBSA. All Loans.
More unemployment shock categories

	(1)	(2)
Rel. High Unemp. $\times$ equity $\leq -20\%$	1.10***	0.57***
	(10.44)	(5.33)
Rel. High Unemp. $\times$ equity $(-20, 0)\%$	0.43***	0.18***
	(6.60)	(2.64)
Rel. High Unemp. $\times$ equity $[0, 20)\%$	excluded group	excluded group
Rel. High Unemp. $\times$ equity $\geq 20\%$	–0.41***	–0.15***
	(–7.95)	(–2.78)
Ave. Unemp. $\times$ equity $\leq -20\%$	0.81***	0.43***
	(8.41)	(4.34)
Ave. Unemp. $\times$ equity $(-20, 0)\%$	0.44***	0.22***
	(9.41)	(4.45)
Ave. Unemp. $\times$ equity $[0, 20)\%$	excluded group	excluded group
Ave Unemp. $\times$ equity $\geq 20\%$	–0.04	0.04
	(–1.16)	(1.13)
Rel. Low Unemp. $\times$ equity $\leq -20\%$	–0.01	–0.22
	(–0.03)	(–0.50)
Rel. Low Unemp. $\times$ equity $(-20, 0)\%$	0.27**	0.09
	(1.97)	(0.63)
Rel. Low Unemp. $\times$ equity $[0, 20)\%$	excluded group	excluded group
Rel. Low Unemp. $\times$ equity $\geq 20\%$	–0.16**	–0.09
	(–2.05)	(–1.20)
Lagged change in equity		–4.65***
		(–13.28)
Subprime score		0.52***
		(12.72)
Near prime score		0.21***
		(6.63)
ZIP $\times$ year effects	Y	Y
Individual effects	Y	Y
No. obs.	4068842	4068842
No. clusters	5627	5627

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, and 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 $t-1$. See Section 3.2 for a detailed variable description. $D_{zt-1} \times \mu_{t-1}$ 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 A-6: Moving CBSA. CoreLogic-estimated current equity

Neg. shock × equity ≤ −20%	0.48***	0.42***
	(3.39)	(2.80)
Neg. shock × equity (−20, 0)%	0.06	0.05
	(0.68)	(0.48)
Neg. shock × equity [0, 20)%	excluded group	excluded group
Neg. shock × equity ≥ 20%	0.14	0.15
	(1.48)	(1.61)
Pos. shock × equity ≤ −20%	0.34	0.28
	(1.64)	(1.31)
Pos. shock × equity (−20, 0)%	–0.02	–0.04
	(–0.16)	(–0.33)
Pos. shock × equity [0, 20)%	excluded group	excluded group
Pos. shock × equity ≥ 20%	0.38***	0.39***
	(3.46)	(3.52)
Subprime score		0.43***
		(4.58)
Near prime score		0.18**
		(2.30)
Lagged change in equity		–0.30
		(–1.10)
ZIP × year effects	Y	Y
Individual effects	Y	Y
No. obs.	627140	627140
No. clusters	8568	8568

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, zero otherwise, and 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 3.2 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.

Table A-7: 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 A-8: 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 ≤ −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 ≤ −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 ≥ 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 ≤ −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 ≤ −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 ≥ 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 A-9: MOVING IN THE MODEL. INDIVIDUAL REGRESSIONS WITH ACTUAL EQUITY. (OWNERS WITH POSITIVE MORTGAGE BALANCE, AGED 25–60)

	STRONG REGIONS				WEAK REGIONS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployed × equity $\leq -20\%$	9.94***	10.03***	5.09**	5.13**	21.52***	21.58***	15.83***	15.83***
	(4.28)	(4.35)	(2.25)	(2.29)	(6.50)	(6.55)	(4.88)	(4.90)
Unemployed × equity $(-20, 0)\%$	9.92***	10.02***	6.43***	6.47***	18.75***	18.82***	14.55***	14.54***
	(6.14)	(6.25)	(4.13)	(4.20)	(9.79)	(9.84)	(7.68)	(7.68)
Unemployed × equity $[0, 20)\%$	2.44**	2.44**	2.06*	2.06**	6.16***	6.16***	5.49***	5.49***
	(2.39)	(2.39)	(2.05)	(2.06)	(4.02)	(4.03)	(3.73)	(3.73)
Unemployed × equity $\geq 20\%$	4.92***	4.91***	5.00***	5.00***	9.85***	9.85***	9.95***	9.95***
	(8.52)	(8.51)	(8.78)	(8.78)	(15.99)	(15.93)	(15.99)	(15.95)
Employed × equity $\leq -20\%$	4.20***	4.30***	–0.26	–0.22	4.24***	4.30***	–0.93	–0.93
	(5.46)	(5.53)	(–0.35)	(–0.29)	(5.32)	(5.38)	(–1.22)	(–1.22)
Employed × equity $(-20, 0)\%$	2.02***	2.12***	–0.17	–0.14	1.96***	2.03***	–0.60**	–0.61**
	(7.16)	(7.28)	(–0.81)	(–0.59)	(6.11)	(6.44)	(–2.42)	(–2.47)
Employed × equity $[0, 20)\%$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Employed × equity $\geq 20\%$	–0.39**	–0.40**	–0.32*	–0.32*	–0.61***	–0.61***	–0.54**	–0.54***
	(–2.23)	(–2.30)	(–1.80)	(–1.83)	(–3.14)	(–3.21)	(–2.78)	(–2.79)
Lagged change in equity		1.07*		0.36		0.72		–0.08
		(1.77)		(0.58)		(0.94)		(–0.11)
Foreclosure			4.96***	4.96***			5.79***	5.80***
			(12.55)	(12.44)			(17.35)	(17.21)
Region × Year effects	Y	Y		Y	Y	Y	Y	Y
Individual Effects	Y	Y	Y	Y	Y	Y	Y	Y
No. obs.	95510	95510	95510	95510	94511	94511	94511	94511
No. clusters	27	27	27	27	27	27	27	27

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $M_{it} = X_{it-1}\beta + D_z \times \mu_{t-1} + \nu_i + u_{it}$, 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, $D_z \times \mu_{t-1}$ 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 A-10: 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.	1534325	1534325	1534325	1534325
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7. The sample is different from that of Table 7 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, 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 A-11: 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 ≤ −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 ≥ 20%	–0.08	–0.01	–1.89***	–1.87***
	(–1.14)	(–0.11)	(–10.79)	(–10.55)
Local Strong × equity ≤ −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 ≥ 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.	1516695	1516695	1516695	1516695
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7. 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, 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 A-12: Moving in the Model. No Foreclosure

	Predicted Equity		Actual Equity	
	(1)	(2)	(3)	(4)
Local Weak × equity ≤ −20%	0.88***	0.73**	2.95	2.96
	(3.27)	(2.46)	(1.18)	(1.18)
Local Weak × equity (−20, 0)%	0.35*	0.26	1.12***	1.12***
	(1.77)	(1.35)	(5.06)	(5.08)
Local Weak × equity [0, 20)%	excluded group	excluded group	excluded group	excluded group
Local Weak × equity ≥ 20%	–0.13	–0.06	–0.23	–0.25
	(–0.84)	(–0.40)	(–0.74)	(–0.75)
Local Strong × equity ≤ −20%	0.95***	0.80**	3.41	3.43
	(3.31)	(2.65)	(1.26)	(1.26)
Local Strong × equity (−20, 0)%	0.38***	0.29**	0.68***	0.68***
	(2.88)	(2.08)	(3.82)	(3.86)
Local Strong × equity [0, 20)%	excluded group	excluded group	excluded group	excluded group
Local Strong × equity ≥ 20%	–0.09	–0.02	0.02	–0.00
	(–0.66)	(–0.16)	(0.08)	(–0.00)
Lagged change in equity		–0.69		0.05
		(–1.56)		(0.43)
Region × year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	187654	187654	187654	187654
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7 except that foreclosure is not allowed. 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. 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 A-13: 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.	188808	188808	188808	188808
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7 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, 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 A-14: 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.	188961	188961	188961	188961
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7 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, 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 A-15: 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.	196413	196413	196413	196413
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7 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, 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 A-16: 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.	189183	189183	189183	189183
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7 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, 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 A-17: 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.	192238	192238	192238	192238
No. clusters	54	54	54	54

Notes: Model parameters as in Table 7 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, 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.

B Further Details on the Model

B.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 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):

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

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 house value and deposits, respectively. Individuals who default lose their home and their home equity (if any) but discharge all mortgage debt.
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 remains employed; if $l_s^e = 2$, the individual becomes unemployed, and for $l_s^e = 3$, a non-local offer is received. If $l_s^u = 1$, the unemployed individual does not receive any offers; if $l_s^u = 2$, a local offer is received, and if $l_s^u = 3$, a non-local offer is received. l evolves as follows:

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

For a homeowner to accept a non-local offer, the owner must sell the home and become a renter for one period.[44]

The houseprice 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):

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

B.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

[44]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.[45] 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).

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

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

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

[45] 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:

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

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

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.

C 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 home ownership. We compute average utility for the alternative parameterizations of the model in the same fashion and compare $\overline{u}^B$ to $\overline{u}^A$.[46]

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 C-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

[46] 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.

median—and 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 loses 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 C-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 45-64	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.