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

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Abstract

Using credit report data from two of the three major credit bureaus in the United States, we infer with high certainty whether households move to other labor markets defined by metropolitan areas. We estimate how the patterns of moving relate to labor market conditions, personal credit, and homeownership using panel regressions with fixed effects which control for all constant individual-specific traits. We interpret the patterns through simulations of a dynamic model of consumption, housing, and location choice. We find that households with negative home equity move more than other households, in particular when local unemployment growth is high—overall, negative home equity is not an important barrier to labor mobility.

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1 Introduction

The severe drop in house prices during and after the Great Recession which started in late 2007 may have hampered structural 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. If such reluctance keeps workers from moving from depressed areas to areas with available jobs, the Beveridge curve, which depicts the relation between vacancies and joblessness, may shift out. For example, *the Economist*, August 28, 2010, tells this story in an article predicting higher structural unemployment in the United States (page 68, and leader page 11). However, hard evidence is not easy to come by. Using credit report data, we provide evidence that labor market adjustment in the United States is not significantly hampered by households with negative home equity being unable to move to better job prospects.

We use data from two leading credit bureaus in the United States. We obtained one dataset from TransUnion—this dataset contains credit information for borrowers with non-agency securitized mortgages. It is merged with another major dataset, the loan-level LoanPerformance (LP) Securities database provided by CoreLogic. The LP database contains information on loan and borrower characteristics at mortgage origination and monthly loan performance for about 90% of all subprime, Alt-A, and prime non-agency securitized mortgage loans.[1] It is the main database used by institutional investors for analyzing the underlying collateral of non-agency mortgage-backed securities. We obtained another dataset, the Consumer Credit Panel based on credit report data from Equifax, through the Federal Reserve Bank of New York. This is a representative sample of borrowers for which we know credit characteristics and some demographic information.

For each loan in the LP dataset, we observe most of the underwriting criteria measured at the time of loan origination: credit scores, debt-to-income ratios, and loan-to-value ratios. Also, for each mortgage we know the location of the property (ZIP code), and the monthly performance after securitization. The LP dataset contains an extensive list of loan characteristics but does not contain borrowers' credit information. CoreLogic and TransUnion accurately matched their databases and created a dataset called Consumer Risk Indicators for RMBS.[2] We use this dataset because both mortgage-level and borrower-level attributes are available for each mortgage loan. Importantly, we can estimate home equity for each mortgage loan using loan-to-value ratios at origination for each mortgage loan and subsequent house price changes in the area (ZIP code).

[1] Subprime mortgages are considered risky loans because they are typically originated to individuals with impaired credit history. Prime mortgages in this dataset are primarily jumbo loans, which are mortgages with balances larger than Freddie/Fannie Mae's conforming limits. Alt-A mortgages are loans usually originated to borrowers with good credit histories but under less strict underwriting criteria (no-doc loans, for example). Most subprime mortgages were originated between the years 2000 and 2006. Many homeowners with these types of loans have negative equity.

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

For brevity, thereafter, we will label the two datasets described above as TransUnion and Equifax, respectively. The results based on the two credit bureau datasets should not be directly compared as they represent different segments of the U.S. population.

From credit reports we can infer with high certainty whether households move. We merge these datasets with labor market data at the CBSA-level (Core Based Statistical Area, a collective term for both metropolitan and micropolitan areas) and the state-level from the Bureau of Labor Statistics and with ZIP code level house price indices from CoreLogic, which allows us to relate mobility to unemployment and house-price appreciation in the local area (ZIP code). We then ask if falling house prices limit outward mobility and, in particular, if the effect is important for individuals with negative home equity. We find no evidence of a lock-in effect: in the TransUnion dataset, borrowers with negative equity are more likely to move out of metropolitan areas/states than other borrowers, suggesting that the opportunity to get a (better) job dominates considerations related to housing equity when local employment opportunities are scarce. A similar, although less significant, pattern is found using the Equifax dataset.

There is a growing body of research, both empirical and theoretical (described in more details in the Section 2), which analyzes the relationship between housing and unemployment. There is, however, hardly any consensus in the literature. The data used in previous studies are either from the American Housing Survey, which follows housing units rather than individuals, or from the American Community Survey, which reports numbers aggregated to the county level. A notable difference between our study and previous studies is that our micro data from credit reports allow us to perform estimations controlling for unobserved heterogeneity, such as whether a person has a certain psychological disposition which is correlated with both homeownership and mobility, by including person-specific fixed effects in our regressions. Also, certain consumers may be inherently less mobile than the average consumer and inherently have a low propensity to save and accumulate home equity. We assume that changes in the level of house prices, in the ZIP code in which a consumer resides, are exogenous to the consumer after aggregate effects have been controlled for. However, even ZIP-level exogenous shocks may not provide correct identification unless unobserved individual characteristics are controlled for. When house prices fall, consumers with low savings will disproportionately end up with negative equity and, if they are also less mobile, a researcher may infer a causal effect of low home equity on mobility while the true pattern is one of certain people systematically accumulating less equity and moving less. In order to hedge against such selection effects, one needs access to panel data such that individual-specific effects can be controlled for. Our data allow us to control for potential heterogeneity and our estimations are therefore less likely to capture spurious patterns. Credit report data are particularly likely to deliver precise information about long-distance moves.[3]

[3]People may change their mailing address from, say, their home to their office or to a mailbox so the credit report data is not proof against measurement error in short-distance mobility. However, our main focus is on mobility

We infer household mobility and directly measure borrowers' home equity. This allows us to reconcile the different findings in the literature and determine if low home equity prevents individuals from moving to high-employment regions—i.e., whether weak housing markets hamper geographical labor market restructuring, thereby prolonging recessions. To help us interpret the patterns in the data, we simulate a dynamic model of consumption, housing, and location choice in the presence of unemployment. In the model, homeowners who are unemployed and receive job offers from other locations are more likely to move than other groups of households regardless of home price depreciation. However, the model matches the data in that it predicts higher mobility out of regions with both low home equity and weak labor market conditions.

The paper is organized as follows. Section 2 reviews the extant literature. Section 3 describes our empirical specification and results, while Section 4 describes our model, its calibration, and the results of various experiments. Section 5 concludes.

2 Literature Survey

Oswald (1997) suggests that homeownership impacts labor market clearing because high costs of selling and buying houses limit geographical mobility. Oswald's paper has been very influential, and the notion that homeownership leads to higher unemployment rates or longer duration of unemployment spells has become known as the Oswald hypothesis. While Green & Hendershott (2001) confirm this result (although they find that only prime age individuals are subject to lock-in), Munch, Rosholm & Svarer (2006) do not find much support for the hypothesis of limited geographical mobility of homeowners using Danish micro data. In a later study, Munch, Rosholm & Svarer (2008) find a negative impact of homeownership on job-to-job mobility.[4] Coulson & Fisher (2009) compare several models of homeownership and mobility and study the patterns of labor market outcomes and housing tenure choices across U.S. CBSAs using micro data from the Current Population Survey. They conclude that none of the models fits perfectly, but nothing in their results indicates that homeownership is detrimental to welfare although possibly unemployment will increase marginally with homeownership.

Barnichon & Figura (2011) show that the efficiency of the aggregate matching function—the typical relation between hiring intensity and the ratio of vacancies to unemployment—has fallen dramatically following the onset of the Great Recession. They also show that local (defined as industry/geography cells) labor market conditions play a significant role in matching. Barnichon, Elsby, Hobijn & Sahin (2010) find that the drop in matching efficiency was particularly pronounced

between CBSAs. Because the number of people living in one CBSA and receiving mail in another CBSA is small, measurement error is likely to be limited.

[4]Coulson & Fischer (2002) did not find support for the Oswald hypothesis, but their work has been criticized for not controlling for selectivity bias; i.e., that households who are less mobile to begin with self-select into homeownership.

in construction, transportation, trade, and utilities. The decline in house prices and construction activity during the crisis was rather steep in the "sand states" of Arizona, California, Florida, and Nevada. If this concentration in job- and housing-market depressions is associated with low geographical mobility, maybe due to workers being reluctant to sell houses that have lost value, it would partly explain the drop in matching efficiency. Using the Displaced Workers Survey, Schmitt & Warner (2011) confirm that construction workers were displaced more than other workers, but find that displaced construction workers obtain new jobs at the same rate as other displaced workers. Schmitt & Warner (2011) find that displaced workers' frequency of moving to another county or state did not depend on the amount of house-price depreciation in the state, which suggests that underwater mortgages is not a major impediment to mobility of displaced workers.[5]

Ferreira, Gyourko & Tracy (2010)—updated in Ferreira, Gyourko & Tracy (2011)—study the relationship between mobility and negative equity using the American Housing Survey from 1985–2009 and find that people with negative equity in their homes are about 30 percent less likely to move than those with non-negative equity. They argue that, at least in the past, the lock-in effect dominated default-induced mobility. However, Schulhofer-Wohl (2011) questions this finding and argues that the methodology in the previous study is not correct because the authors systematically drop some negative-equity homeowners' moves from the data.

Donovan & Schnure (2011) use data from the American Community Survey 2007–2009 to show that there is a lock-in effect for homeowners who live in areas with large house price declines. The authors, however, find that any lock-in effect emerges almost entirely due to a reduction in within-county mobility. Local mobility is unlikely to be associated with moving to a job; thus, they conclude that housing market lock-in does not cause higher unemployment rates. Chan (2001) reports a reduction in household mobility due to falling house prices while Engelhardt (2003) finds that falling prices do not constrain mobility. Molloy, Smith & Wozniak (2011) suggest that the recent recession and downturn in housing markets played little role in explaining declines of mobility.

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

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

labor market conditions. Head & Lloyd-Ellis (2012) build a full general equilibrium model with search for local and non-local jobs as well as housing. They allow for two types of cities, endogenize housing construction and wages, and calibrate their model to high- and low-wage cities. In their model, homeowners are substantially less mobile than renters and have higher unemployment which implies potentially large differences in unemployment between cities but the effect on aggregate unemployment is minor.

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

A different, quite voluminous, strand of the mobility literature focuses on the income elasticity of geographical mobility. Gallin (2004) stresses the importance of measuring persistence of income shocks correctly because moving decisions will depend on the expected future utility gain from moving. He uses U.S. state-level data to estimate a model of mobility as a function of (state-level) wage shocks and unemployment. For recent contributions see, for example, Bayer & Juessen (2011), who stress that econometric estimates of the potential impact of income gains on migration, when individuals are heterogenous, need to deal with selectivity; i.e., people may already have sorted themselves into (U.S.) states that provide the best fit to their skills (oil exploration workers to Alaska, for example). They estimate that the typical cost of moving between states is in the order of $35,000. Kennan & Walker (2011) formulate a structural dynamic model which takes into account that many people move more than once—even back to their original state—and estimate the model using micro data from the U.S. National Longitudinal Survey of Youth. Among their findings is that mobility declines with age and this is partly, but not fully, explained by young individuals obtaining larger lifetime income gains from moving (the "human capital" or "investment" model of migration). College graduates move substantially more than non-college graduates.

Our contribution complements the literature on potential lock-in from low or negative housing equity by focussing directly on whether workers are less likely to move from locations with worse job prospects due to negative equity. Our work is also part of an emerging literature using credit-bureau microeconomic data to answer pivotal questions in macroeconomics. Examples include Mian & Sufi (2009) and Mian & Sufi (2010), who document that homeowners who borrowed heavily against their home equity as house prices rose before the Great Recession defaulted in large numbers when house prices declined.

3 Data, regression specifications and results

3.1 Data

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

The first dataset, called TransUnion Consumer Risk Indicators for RMBS, contains a set of about 300 credit characteristics for anonymized consumers who had at least one non-agency securitized mortgage at any point in time between April 2005 and December 2010. Using this dataset we know, at the individual-level, what kind of debt and how many accounts consumers had, and how they managed payments on their accounts. We also have, for each consumer in the dataset, monthly credit scores and updated ZIP codes of a mailing address. This allows us to determine with great certainty if an individual changes his or her residence. Most importantly, this dataset was accurately merged (by the credit bureau) with the mortgage loan-level LoanPerformance (LP) Securities database provided by CoreLogic, which allows us to measure home equity.[6]

The LP dataset contains information about mortgages at origination and after securitization for over 90% of all U.S. non-agency securitized mortgages (subprime, Alt-A, and jumbo prime). The dataset includes some 20 million loans in the subprime and Alt-A market and about 4.4 million jumbo prime loans. For each mortgage loan in the LP dataset, we observe the borrower's credit score, owner occupancy, and loan-to-value ratios at mortgage origination. In addition, we know the ZIP code for the property location, which is not necessarily the same as an individual's mailing address. Property ZIP codes allow us to merge individual-level data with macro data on house prices, population, income, and employment in the areas where people live. We use reported loan-to-value ratios at mortgage origination together with subsequent house price changes at the ZIP code level to calculate whether and how much mortgages are "underwater" (i.e., having negative home equity because mortgage balances exceed the value of the home).

Our main cleaning restrictions in TransUnion data are the following. First, we drop those 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. The purpose of this restriction is to eliminate individuals who hold their properties for investment purposes.[7] We further drop

[6]The matching algorithm keys off of overlapping load data between the two databases. Actual borrower names and addresses are used to minimize false positive matches generated by the algorithm. The match rate is exceptionally high in comparison to other matched databases studied in the literature. The match rate of open loans in LP data to credit data is currently 93% with less than 1% false-positive. The match rate for closed loans is currently 73%.

[7]Although LoanPerformance reports if an individual's loan was taken for investment purposes, some individuals may still misreport the purpose of their mortgage loan. This restriction also eliminates borrowers who live at their

observations if the balance-to-limit ratio on all mortgages is either zero or missing. We do so to eliminate borrowers who closed their loan at time $t-1$ and who are potentially renters at time $t-1$, and those borrowers who paid out their mortgages, for whom considerations of mortgage debt are no longer present when they decide to move. Finally, we drop individuals who foreclose in spite of having equity of more than 20% of the value of their home. This latter restriction eliminates a few individuals for whom measurement error in equity is likely to be substantial. We then randomly select 20% of borrowers from the TransUnion-LP dataset for our analysis.

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

The loans in TransUnion may not be representative of the entire U.S. mortgage market due to the characteristics outlined above.[8] To check if our analysis is robust and the results are applicable to the entire country, we analyze data from another credit bureau, Equifax. The Equifax Consumer Credit Panel dataset (Equifax), available to us from the Federal Reserve Bank of New York, is an anonymized 5% random sample of individuals who have a social security number and use credit in some form in the United States.[9] Individuals who were selected randomly are labeled as "primary." Each quarter from 1999:Q1 to 2010:Q4, a wide range of credit characteristics is reported for approximately 12 million "primary" individuals. Credit characteristics for everybody residing at the same address as "primary" individuals are included in the data so the total number of people in the dataset each quarter is approximately 40 million (about 15% of the US population). There are more than 600 credit attributes reported for each consumer in this dataset. Among the attributes, similarly to what is available for TransUnion, there are credit scores and the number

properties but receive mail at some other place, like their business address, but we perform a similar restriction in Equifax data dropping observations for individuals who report their mailing address to be other than a street address.

[8]TransUnion also has a dataset representative of the entire country but this dataset is not matched with mortgage data and is not available to us.

[9]For a more detailed description of the data see Lee & van der Klaauw (2010).

and performance of each credit obligation: auto loans, credit cards, home equity loans, mortgages, etc. In addition, we know individuals' ages and the age of their accounts.

When using Equifax, we exclude individuals if their mailing addresses are classified as military, post office, or firm (business) address as some people prefer to receive their mail, for example, at work instead of their home address. We also drop individuals who report their mailing address to be a non-street address. We focus on individuals who have at most one open first-lien mortgage (over 90 percent of the sample of homeowners) with a positive balance, and who are of ages 20–60. Since we do not observe the amount of home equity nor details about individual mortgages (these characteristics are only available in the combined TransUnion-LP dataset), we rely on house-price appreciation since origination in the ZIP code of the homeowner's residence (mailing address) to construct a proxy for home equity. We further restrict the sample to borrowers whose mortgages were relatively recently originated, after year 1999. We show results for the cleaned full Equifax Credit Panel and for various subsamples constructed to be better able to capture homeowners with negative equity. In one subsample, we limit the data to mortgages that were originated after 2005. The majority of these are expected to have negative equity during and after the crisis. In a second subsample, we limit the data to individuals who have paid back less than 95% of the original mortgage amount. Such loans will typically, by construction, be relatively recent. For these, declines in house prices most likely will lead to a negative equity position. In a third subsample, we limit the data to ZIP codes with above average numbers of TransUnion mortgages relative to Equifax mortgages.[10]

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

3.2 Variable Definitions

We construct the following dummy variables which capture shocks to households' employment possibilities in the area of their residence for individuals with different levels of home equity. Let

[10] Specifically, we calculate the ratio of the number of mortgages in the TransUnion sample to the Equifax sample for each ZIP code and keep the ZIP codes for which the ratio is above the 90th percentile value. Equifax contains subprime, Alt-A, and jumbo prime mortgages as in TransUnion, as well as other types of loans available in the mortgage market, and a high number for the ratio indicates that a ZIP code contains a large number of subprime loans as those represent the majority of loans in TransUnion data.

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

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

Δu_{rt} denote the change in the annual unemployment rate in region r at time t and Δu_t as 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 if the regional shock is positive or negative (i.e., relatively weak local labor market conditions or relatively strong local labor market conditions). When the regional shock is positive, the dummy variable "Neg. shock" takes the value of one while the dummy variable "Pos. shock" equals one if Shock^u_{rt} takes a negative value. That is, a positive value for the regional shock, i.e., when the regional unemployment grows faster than the national unemployment, is labeled a negative shock to the local economy. For examining robustness, we define similar dummies (with the signs properly adjusted) for changes in local employment and local vacancy rates (vacancy rates are based on the help-wanted data from the Conference Board).

The TransUnion dataset—when merged with ZIP code level home values and loan-to-value ratios at mortgage origination—allows us to directly test if there is an impact of negative equity on the probability of moving out of local labor markets. Similar to Demyanyk, Van Hemert & Koijen (2011), we define housing equity for property i at time t as:

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

where we proxy the change in the value of an individual property since origination ($\text{Value}_{i,0}$) by the change in the ZIP code level of house price indices between 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. A dummy variable "Equity $\leq -20\%$" equals one if home equity is negative in an amount that exceeds 20% of the house value while "Equity $(-20, 0)\%$" equals one if home equity is negative, but numerically less than 20% of the house value. Similarly, dummy variables "Equity $[0, 20\%)$" and "Equity $\geq 20\%$" equal one if home equity is positive but low (between 0 and 20%) or above 20% of the home value, respectively. We interact each of the dummy variables for regional shocks with the equity dummies. As a result, we obtain eight dummy variables. In our empirical analysis, out of the eight categories, we omit the two dummies for homeowners with positive but small equity. Table 1 summarizes these dummy variables along with the other variables we use in our empirical analysis.

For the analysis based on Equifax, we cannot measure home equity because we do not know financial details of mortgages at origination or thereafter. To proxy for home equity, we use the cumulative growth in house prices ("HP growth") since mortgage origination in the ZIP code where an individual lives. We construct dummy variables "HP growth $\leq -20\%$," "HP growth $(-20, 0)\%$," "HP growth $[0, 20\%)$," and "HP growth $\geq 20\%$" defined similarly to the corresponding dummies for equity in the TransUnion dataset. We also interact these variables with the dummies "Pos. shock" and "Neg. shock" to explore if negative equity, likely resulting from declining house prices in the area of residence, hampers mobility out of areas that experience negative employment shocks.

In our analysis, we use several other control variables: foreclosure indicators, the age of the mortgage and credit scores. In Transunion, a "Foreclosure" dummy equals one if a mortgage (from the LP data) is in foreclosure in year t. In Equifax, a "Foreclosure" dummy equals one if a consumer had at least one property in foreclosure in the past 24 months. "Mortgage age" in both datasets is the number of months between t and the month of mortgage origination. We control for consumers' credit scores by including the variable "Log Score," which is the lagged logarithm of TransUnion's credit score called the Vantage Score or the lagged logarithm of Equifax's credit score called the Risk Score. These credit scores have the following ranges: the Vantage Score ranges from 501 to 990, and the Risk Score from Equifax ranges from 280 to 850. In our analysis based on TransUnion, "Subprime score" and "Near prime score" are dummy variables that equal one if the Vantage Score variable takes values below 641 and between 641 and 700, respectively.[13] When using Equifax data, we construct these dummies using the ranges below 661 and between 661 and 700, respectively.[14]

In the TransUnion dataset, we are able to observe if a mortgage was originated for investment purposes or for owner occupancy. We use this information to create a dummy "Investment purpose" that equals one if a consumer bought a property primarily for investment purposes. Most of the loans in the TransUnion dataset are either subprime or Alt-A.[15] About half of those were short-term hybrid mortgages, which are typically very short-lived. We estimate our regressions for subsamples

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

[14] Equifax uses the 660 cut-off point in identifying borrowers with "subprime" scores. For details, see the document available from the following link: http://news.equifax.com/index.php?s=18010&item=96773. The following Equifax study defines consumers with scores above 700 as having "prime" scores: http://finance.yahoo.com/news/credit-loosens-subprime-consumers-040132876.html

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

that separate different segments of the market (prime, subprime, and Alt-A) and different type of mortgages (Neither Investment Nor (short-term) Hybrid).

3.3 Moving Rates

Table 2 shows that moving rates declined substantially from 2007 to 2009. As shown in the top panel of Table 2, the overall moving rate, computed as a change in ZIP code, declined from approximately 4.3% to 3.3% for Equifax households, and from about 7% to 5.5% for TransUnion households (bottom panel of the table). The moving rate across CBSAs declined from about 1.4% to 1.0% in Equifax and from 2.7% to 1.8% in TransUnion. The moving rate from one state to another declined from 1.0% to 0.75% in Equifax and from 1.8% to 1.1% in TransUnion. TransUnion households are predominantly subprime borrowers, which might explain why moving rates differ across the two datasets.[16]

3.4 Regression Specification and Results

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

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

where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise. $\delta_j \times \mu_t$ denotes (lagged) region (CBSA/state) fixed effects interacted with year dummies, and ν_i are individual fixed effects. X is a vector of regressors of which the most important are the interactions of home equity with labor market conditions for the area where consumer i resides. We summarize this information in the form of the following dummies: Neg. shock $\times$ equity$_{\leq -20\%}$, Pos. shock $\times$ equity$_{\leq -20\%}$, Neg. shock $\times$ equity$_{(-20,0)\%}$, Pos. shock $\times$ equity$_{(-20,0)\%}$, Neg. shock $\times$ equity$_{\geq 20\%}$, and Pos. shock $\times$ equity$_{\geq 20\%}$. Due to the presence of CBSA $\times$ year dummies the interactions Neg. shock $\times$ equity$_{(0,20)\%}$ and Pos. shock $\times$ equity$_{(0,20)\%}$ are omitted in order to avoid perfect multicollinearity.

Other controls include a foreclosure indicator, and credit scores. Explanatory variables are lagged one year for the analysis to reflect credit or labor market conditions before the decision to move is made. We cluster standard errors by individuals in the regressions.

In the regressions, CBSA $\times$ year dummies remove all effects that are common to all individuals in a given CBSA in a given year; in particular, common local labor market unemployment and

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

house-price shocks. However, homeowners with more or less housing equity, facing a negative or positive shock to local unemployment, have different mobility rates and our results are identified from differences between people with different levels of equity in each CBSA in each year.[17] This way, for example, the coefficient to Neg. shock $\times$ equity$_{\leq -20\%}$ is identified from the difference to individuals with low positive equity facing a negative shock.[18]

3.4.1 Results: TransUnion

Table 4 displays our main results based on unemployment rates as labor market indicators. As previously discussed, all regressions include CBSA/state $\times$ year fixed effects and, importantly, individual fixed effects which control for all non time-varying individual traits. (We report the correlation matrices with individual fixed effects removed from each variable in Table 3 and without removing individual fixed effects in the Appendix, Table A.1.) The top eight regressors in the Table 4 are our main variables of interest. The top two regressors are interactions of local labor market conditions with the dummy for very negative equity, the next two are interactions of labor market conditions with the dummy for moderately negative equity, the fifth and sixth regressors are the left-out dummies for the groups of people with low but positive equity facing a negative and positive regional shocks, respectively, and the seventh and eighth regressors comprise interactions of the dummy for equity above 20 percent of house value and local labor market conditions. We focus on non-local mobility: moving to another CBSA or, alternatively, moving to another state. We believe that moving across CBSAs or states to a large extent proxies for job-related moves—for example, Ferreira et al. (2011) report that the majority of interstate moves are job-related. It should be kept in mind that due to the inclusion of individual fixed effects all variables are identified by changes over time so, for example, the coefficients to the low equity dummies are identified from people who are not in that group throughout.

It is immediately obvious that individuals with very negative equity are more likely to move than individuals with low positive equity. From the first column of Table 4, for CBSA moves, not including control variables, we see that compared to the left-out group, individuals with very negative equity positions are 0.65% more likely to leave their CBSAs when unemployment increases (relative to U.S. unemployment) and 0.34% more likely to leave CBSAs with falling unemployment. The coefficients for this equity group increase when individual-level controls are included, but clearly low equity individuals in this sample are not locked-in because they are underwater with their mortgages. Individuals with high positive equity are also relatively more mobile although this finding is not robust to the inclusion of controls. Mortgage age is highly significant, although

[17]In the regressions using Equifax data, the identification comes from differences in house price growth between ZIP-codes within the same CBSA.

[18]Because a CBSA faces either a negative or positive shock in a given year, no coefficient of our interactions of interest will be identified from variation across CBSAs or even across good versus bad years within the same CBSA.

this is likely a mechanical finding specific to the subprime sample as many subprime mortgages feature a penalty for early repayment. Foreclosure, not surprisingly, is also a highly significant predictor of inter-CBSA mobility. Credit scores negatively correlate with mobility. The patterns are qualitatively similar for interstate moves although the estimated coefficients to the main variables are lower for interstate moves for individuals with very negative equity.

The results point clearly to lack of housing lock-in. Our interpretation is that the potential costs associated with disposing of an underwater property are outweighed by the benefits of obtaining a job. Our results do not imply that a decrease in property values, and thereby equity, holding everything else constant would increase mobility, because individuals with low equity in our sample may at the same time be unemployed and more prone to move in order to obtain a job—but this could be because they are unemployed and not because they hold low equity. However, our results do imply that negative equity does not have a dampening effect on mobility which dominates other features with which it may be correlated. We return to the interpretation of the results in the theoretical section.

The following tables examine the robustness of our results in detail. Table 5 focusses solely on CBSA moves and includes individual-level controls in all columns. The first column displays results when investment properties, as identified by CoreLogic in the LP dataset, are dropped. The results are virtually unchanged from the corresponding column of Table 4. In the second column, (individuals holding) investment loans or (short-term) hybrid loans are dropped. The results are similar except that the high equity group now is insignificantly different from the left-out group. In the column labeled "Subprime," where other than subprime loan types are dropped from the sample, the results are very similar to those of the other columns although mobility decreases faster with improvement in credit scores.[19] In the column "Subprime Score," we focus on individuals with a credit score below 641 in the first year they are observed in our sample and find results similar to our CBSA results in Table 4, except individuals with high equity are no more mobile than those in the left-out group. One might also notice that individuals' mobility increases if they improve their scores enough to move out of the subprime category. The next column considers individuals with Alt-A loans—the overall mobility patterns are similar to that of subprime borrowers. The last column displays results for prime borrowers, who, in this sample, mainly are individuals with jumbo loans. The patterns regarding equity is similar for this group, although this sample in general consists of individuals who are quite different from those of the subprime sample. Mortgage age is a much stronger predictor for this group but that is partly because this sample drops borrowers whose loans tend to get refinanced early. Mobility increases quite significantly when individuals in this group drop into the subprime category while the effect of a marginal increase in the score is immaterial for these individuals who are already prime.

[19] The coefficient to mortgage age is smaller, which likely is due to most subprime loans being of low age as found by Demyanyk (2009).

Table 6 examines robustness along other dimensions while focussing on CBSA mobility for the full TransUnion subsample. The first column considers only individuals living in non-recourse states where lenders cannot pursue defaulting borrowers for losses beyond the collateral (house) pledged.[20] It may be more tempting for borrowers to foreclose in such states, although lenders in other states often do not pursue borrowers in default because the borrowers don't normally hold other assets of significance. The results are again similar to those we found earlier except the relatively higher mobility of individuals with very negative equity is more pronounced in CBSAs with positive labor market shocks. In the second column, we consider all states but use the number of vacancies in the CBSA as the measure of economic conditions in the local labor market. The results are similar to our baseline results as are the results, in the third column, where employment in the CBSA is used as the measure of local conditions.

Table 7 considers a regression similar to those reported in the previous tables but, instead, interacting labor market conditions with house price growth over the previous two years and cumulative house price growth since origination, rather than equity. Strong house price depreciation will lead to many owners being underwater and we display the results of such regressions, using the representative Equifax data, in the the next subsection. We want to examine if the TransUnion sample is typical, and in order to directly compare results from the two datasets we display results on the TransUnion sample using the same variables as are available in Equifax. The results for cumulative house price growth in Table 7 are qualitatively similar to the previous tables with negative house price shocks being positively correlated with out-migration. The patterns are less significant as one would expect if equity is the variable of interest and house price growth is an imperfect indicator of home equity since measurement error embedded in a proxy for the equity regressor will bias the coefficient toward zero. Overall, the regressions do not indicate lock-in for owners of underwater properties. The results with cumulative house price growth correspond better with the results using equity so we focus on this variable in our regressions using the Equifax dataset.

3.4.2 Results: Equifax

Table 8 reports results from regressions similar to the one presented in Table 7, at the CBSA-level, but using Equifax data. Equity is not available, so we use cumulative house price growth since mortgage origination. The first column, which presents results from the full cleaned Equifax sample, has very few significant coefficients, although foreclosures and mortgage age both are positive and highly significant. These results, of course, do not point to home equity as playing any role in (lack of) labor market clearing, but we would like to ascertain that the results which

[20]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.

we found using the TransUnion data are robust for the population segment that dominates that data: people with recent mortgages, low equity at origination, in ZIP codes with many TransUnion mortgages (which, typically, were the ZIP codes in states such as Arizona and California, whose housing markets were hit the hardest in the Great Recession).

In the second column, we restrict the sample to borrowers with mortgages originated since 2005. The results regarding equity (approximated by cumulative house price growth) are very similar to those found using the TransUnion sample. In the third column, we restrict the sample to borrowers with little debt repayed on their mortgage.[21] The results are quite similar to the full sample, except the group with high equity is significantly less likely to move. One may conjecture that individuals that started with little equity and now have high equity (approximated by house price growth) reside in ZIP codes where job prospects are relatively good. The fourth column restricts the sample to ZIP codes with relatively many subprime mortgages. For this sample, we find results similar to those found for the TransUnion sample, which demonstrates that the pattern of high mobility for owners with large negative equity is not an artifact of TransUnion's sampling but rather a systematic pattern in ZIP codes with large numbers of recently originated or subprime loans.

4 The model

In order to interpret our findings, we construct a model with the following key features: (1) homeownership is a choice for households, (2) households can be employed or unemployed, (3) unemployed households may reduce the duration of unemployment by moving, (4) employed workers may improve their earnings potential if they move elsewhere, (5) moving is costly, particularly for homeowners who face important transaction costs, (6) foreclosure is permitted. Our model builds on Díaz & Luengo-Prado (2008) and Guler & Taskin (2011). Households have finite life-spans and derive utility from consumption of a nondurable good and housing services that can be obtained in a rental market or through homeownership. House buyers pay a down payment, buyers and sellers pay transactions costs, housing equity above a required down payment can be used as collateral for loans, and foreclosure is allowed. There are no other forms of credit, tax treatment of owner-occupied housing is preferential as in the United States, and households face uninsurable earnings risk and uncertainty arising from house-price variation.

Preferences and demography. Households live for up to T periods and face an exogenous probability of dying each period. During the first R periods of life they receive stochastic labor earnings and from period R on they receive a pension. When a household dies, it is replaced by a newborn

[21] The amount of down payment a borrower made at mortgage initiation is not reflected in this measure. Thus, it does not directly measure equity.

and its wealth (if positive) is passed on as a bequest. Houses are liquidated at death so newborns receive only liquid assets. We assume warm-glow altruism.

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

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

When buying a house, households pay a down payment $\theta q_t H_t$. Therefore, a new mortgage must satisfy the condition $M_t \leq (1-\theta)\, q_t\, H_t$. For homeowners who do not move in a given period, houses serve as collateral for loans (home-equity loans) with a maximum loan-to-value ratio (LTV) of $(1-\theta)$. If house prices go down, a homeowner can service debt if she is not moving. In this case, M_t could be higher than $(1-\theta)\, q_t\, H_t$ as long as $M_t < M_{t-1}$. A homeowner can be "upside-down" (have negative housing equity) for as many periods as the household desires but foreclosure is also an option.

A fraction κ of the house value is paid when buying a house (e.g., sales tax or search costs). When selling a house, a homeowner loses a fraction χ of the house value (brokerage fees). Houses depreciate at the rate δ_h and homeowners can choose the degree of maintenance.[22] Rental housing depreciates at a slightly higher rate ($\delta_h + \varepsilon$, $\varepsilon > 0$) to capture possible moral hazard problems in maintenance. Renters pay no moving costs.

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

Moves can also be the result of foreclosure. Foreclosure is of the non-recourse type. When foreclosing, a household must pay transaction costs, a percentage ρ_y of current income and a small percentage ρ_H of the house value during the foreclosure period. The household must rent for one

[22] 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. We use $\xi = 0.075$ in our baseline calibration.

period and is not allowed to take a job offer in another location during the foreclosure period but there is no additional penalty after that. Homeowners are not allowed to foreclose in the last (possible) period of life.

Earnings and pensions. Households can be working-age or retired. Working-age households can be employed or unemployed and are subject to household-specific risk in labor earnings.

For working-age households, labor earnings, W_t, are the product of permanent income, and two transitory shocks (P_t, ν_t and ϕ_t, respectively): $W_t = P_t \nu_t \phi_t$. ν_t is an idiosyncratic transitory shock with $\log \nu_t \sim N\left(-\sigma_\nu^2/2, \sigma_\nu^2\right)$. $\phi_t = 1$ for employed workers but $\phi_t = \lambda < 1$ for unemployed individuals—i.e., unemployment reduces current income by a certain proportion. In turn, permanent income is $P_t = P_{t-1}\gamma_t \epsilon_t \varsigma_t$. This means that permanent income growth, $\Delta \log P_t$, is the sum of a non-stochastic life-cycle component, $\log \gamma_t$, an idiosyncratic permanent shock, $\log \epsilon_t \sim N\left(-\sigma_\epsilon^2/2, \sigma_\epsilon^2\right)$, and an additional factor, $\log \varsigma$, which is positive for currently employed workers who receive a job offer in a different location and take it, and zero otherwise. Note we do not model geography explicitly but we allow for job offers to arrive from a different location.

Employment status evolves over time as follows: a fraction a_1 of employed workers becomes unemployed each period. Also, a fraction a_2 receives a job offer elsewhere, that workers may or may not take as it requires selling their current home if they are homeowners. These workers remain employed regardless of the moving decision, as do a proportion $1 - a_1 - a_2$ of households who do not fall within the previous two groups. For unemployed workers, a fraction b_1 receives a job offer at their current location and becomes employed next period, a fraction b_2 receives a job offer elsewhere and will be employed next period only if choosing to move, while a fraction $1 - b_1 - b_2$ receives no job offers and remains unemployed for sure. Unemployment spells may have a duration longer than one period because either an unemployed household receives no job offers or because it receives a job offer elsewhere that was not acceptable. Since we do not model geographical locations explicitly, we assume that homeowners believe the region they would be moving to is identical to their current region in terms of the probabilities described above.

Retirees simply receive a pension proportional to permanent earnings in the last period of their working life. That is, for a household born at time 0, $W_t = bP_R$, $\forall t > R$.[23]

House-price uncertainty. House prices are uncertain and, following Li & Yao (2007), house-price appreciation is assumed to be an i.i.d. normal process: $q_t/q_{t-1} - 1 = \varrho_t$, with $\varrho_t \sim N(\mu_\varrho, \sigma_\varrho^2)$. This specification implies that house-price shocks are permanent.[24] House-price shocks are common to residents of the same region. In order to keep the model tractable, there are no built-in house price

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

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

differentials in levels across locations. Our interpretation is that house price differences in levels are fully compensated by income differentials and we abstract from possible strategic moves to locations with cheaper housing on average.[25] Our benchmark specification assumes no correlation between house price shocks and income shocks.

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

4.1 Calibration

The calibration is constructed to reproduce three statistics from the Survey of Consumer Finances (SCF): the homeownership rate, the median wealth-to-earnings ratio for working-age households, and the median ratio of home value to total wealth for homeowners (70 percent, 1.80, and 0.82, respectively). To match the targets, the discount rate is set to 3.99 percent, the weight of housing in a Cobb-Douglas utility function to 0.22, and the minimum house size that consumers can purchase is 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. Some parameters are chosen to match additional targets as explained next.

Preferences, endowments and demography

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

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

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

The curvature of the utility function is $\sigma = 2$.

[25] Halket (2011) considers a model which allows for house price levels to vary across cities but does not study mobility.

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

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

where b measures the strength of the bequest motive, and terminal wealth equals the value of the housing stock, after depreciation takes place and adjustment costs are paid, plus financial assets: $X_t = q_t H_t(1-\delta^h)(1-\chi) + A_t$. r_t^f is the rental price of housing. The Cobb-Douglas utility assumption results in fixed expenditure shares on nondurable consumption and housing services, $\alpha/(1-\alpha)$, by inheritors. The strength of the bequest motive b is set to 0.6.

We follow Cocco et al. (2005) to calibrate labor earnings. Using data from the PSID, these authors estimate the life-cycle profile of income, as well as the variance of permanent and transitory shocks for three different educational groups: no high school, high school, and college. We choose their estimates of the variance of permanent and transitory shocks for households whose head has a high school degree—the typical median household (0.01, and 0.073, respectively).[26] These values are typical in the literature (see Storesletten, Telmer & Yaron 2004). For consistency, we use the estimated growth rate of the non-stochastic life-cycle component of earnings for a household with a high school degree from Cocco et al. (2005). The unemployment replacement rate is set to 60 percent.

In our benchmark case, households who are employed remain employed in the same location with 90 percent probability, become unemployed with a 5 percent probability, and receive a job offer from another location with a 5 percent probability (they can take this offer or refuse it but remain employed in either case). Unemployed workers receive no job offers with a 5 percent probability, become employed in their current location with a 66.5 percent probability and receive a job offer from another location (that they can take or not) with a 28.5 percent probability (i.e., job offers are 70 percent local, 30 percent from another location). This combination produces an average unemployment rate of roughly 5.4 percent. The permanent salary increase associated with a job offer in a different location is 10 percent ($\log \varsigma$) for employed workers but zero for unemployed ones. Note that although we cannot keep track of actual locations in our stylized model, we can potentially play 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.

In our model, retirees face no income uncertainty, and we set their pension to 50 percent of permanent income in the last period of working life. Munnell & Soto (2005) find that the median replacement rate for newly retired workers is 42 percent when using data from both the Health

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

Retirement Survey and the Social Security Administration. Cocco et al. (2005), using PSID data, report that the ratio of average income for retirees to average income in the last working year before retirement is 68 percent. Our choice is in-between these two numbers.

Market arrangements

The minimum down payment is 5 percent, below the 25 percent average down payment for the period 1963–2001 reported by the Federal Housing Finance Board but in line with pre-crisis terms. The buying cost is 2 percent while the selling cost is 8 percent. There is an additional one percent selling cost for non-local moves to capture that moving costs tend to increase with distance and a preference for the current location. The overall moving rate for homeowners in our baseline calibration is roughly 9 percent a year, a bit above the 7 percent figure in TransUnion for 2007–2009. The non-local moving rate for owners is 1.6 percent, in line with the TransUnion and Equifax figures for interstate moves.

The interest rate on deposits, r_a, is set to 4 percent (the average real rate for 1967–2005, as calculated in Díaz & Luengo-Prado 2010), while the interest rate on mortgages is 4.5 percent.

Foreclosure entails a one-period 20 percent loss of current income plus an additional 5 percent of the current value of the home.[27] This combination results in a foreclosure rate defined as the number of households foreclosing in a period over the total number of households of 0.4 percent annually, which is also the foreclosure rate calculated analogously when using the representative Equifax sample of our empirical analysis.

In our setup, there is no age limit on credit availability and in the event of death houses are liquidated using previous period prices to avoid most negative accidental bequests. A negative bequest is still possible for a homeowner who dies at a young age after a period of house-price depreciation but we do not pass along negative (accidental) bequests. Foreclosure is not allowed in the last period of life in order to limit strategic foreclosures at the end of the life cycle.

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.[28] For the period 1989–2004, personal taxes represent 12.47 percent of personal income in NIPA. As in Prescott (2004), this number is multiplied by 1.6 to reflect that marginal income tax rates are higher than average rates. The 1.6 number is the mean ratio of marginal income tax rates to average tax rates, based on TAXSIM (for details, see Feenberg & Coutts 1993). The final number is 19.96 percent, which is approximated with $\tau_y = 0.20$. Mortgage payments are fully deductible, $\tau_m = 1$.

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

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

House prices

House prices follow the process $q_t = q_{t-1}(1 + \varrho_t)$, where $\varrho_t \sim N(\mu_\varrho, \sigma_\varrho^2)$. $\mu_\varrho = 0$ and $\sigma_\varrho^2 = 0.0131$—as in Li & Yao (2007). ϱ_t is serially uncorrelated and uncorrelated with the income shocks. The housing depreciation/maintenance cost rate for owners, δ_h, is set to 1.5 percent, as estimated in Harding, Rosenthal & Sirmans (2007). Housing depreciation is slightly higher for rental units due to moral hazard, $\delta_h + \varepsilon$, 2.2 percent.

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

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

since $E_t[q_{t+1}] = q_t$. This can be interpreted as the user cost for a landlord who is not liquidity constrained, not subject to adjustment costs, and who pays income taxes on rental income. The calibration is consistent with the estimates in Sinai & Souleles (2005), who find the house-price-to-rent ratio capitalizes expected future rents (for more details see Díaz & Luengo-Prado 2010). For our benchmark calibration, r_t^f/q_t is roughly 6.9 percent annually.

Patterns of homeownership and wealth

Figure 2 depicts the evolution of some key variables throughout the life cycle in our baseline calibration. All series are normalized by mean earnings. Panel (a) shows mean labor income (earnings for workers and pensions for retirees) and nondurable consumption. For working-age households, the life-cycle profile for earnings is calibrated to the profile estimated by Cocco et al. (2005) for households with a high school degree. Earnings peak at age 47. For retirees, the pension-replacement ratio is calibrated to be 50 percent of permanent earnings in the last working period. As seen in the figure, our model produces a hump-shaped nondurable consumption profile with a peak around age 60.

Panel (b) in Figure 2 depicts mean wealth and its different components throughout the life cycle. Total wealth is hump-shaped and peaks at ages 60–63, with a value about 4 times mean earnings in the economy, and declines rapidly afterwards. Because there is altruism in the model, total wealth is not zero for those who reach the oldest-possible age. Housing wealth (including collateralized debt) increases until age 52–55, then stays fairly constant until it begins to decrease at age 72, when the homeownership rate starts to decline.

The life-cycle profile of moving rates for homeowners is depicted in panel (a) of Figure 3. We focus on moving rates for owners because renters in the model "move" every period as they can adjust housing services without cost. The average moving rate for homeowners is roughly 9 percent and it declines with age. The overall pattern is similar to that in the Equifax data. This pattern is not surprising because conditional on receiving a non-local job offer, the total gain from higher salaries or escaping unemployment is lower later in life so older households move less for job-related reasons. Panel (b) of Figure 3 depicts foreclosure rates by age (defined as the total number of households foreclosing out of the total number of households). The average in the model is roughly the same as in Equifax (0.3 percent), and in both the model and the data foreclosure rates first increase with age and then decrease. The homeownership rate increases with age, and older households have more home equity. These age-profiles in the model and in the data are not exactly alike, though, with lower foreclosure rates in the model initially and higher rates for middle-age households, probably because the model underestimates homeownership for ages 24–45, and overestimates homeownership rates for older cohorts as panel (c) in Figure 3 depicts. The model is calibrated to reproduce the average U.S. homeownership rate only and it seems we need further heterogeneity and/or additional assumptions to exactly replicate the age-homeownership profile. However, this is not the focus of our paper. The aim is to determine if our empirical findings are consistent with a story in which negative equity does not necessarily lock people in a certain location.

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

We list all benchmark calibration parameters in Table 9.

4.2 The moving decision

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

First, we simulate 27 locations (regions hereafter) with 5,000 people each for 250 periods. House-price shocks are common to all individuals in a given region (we approximate the house price process with three shocks) while income and employment shocks are idiosyncratic. In regions 1 through 9, the house-price shock is at the lowest value for the last three periods of the simulation (housing depreciation). In regions 10 through 18, the house-price shock is at the middle value (constant house prices), while in regions 19 through 27, the house-price shock is at its highest value (housing appreciation). With this setup, there is enough time for some households to end up with negative equity. In the model, households are impatient but prudent and have a clear incentive to pay their mortgages due to the spread between rates for mortgages and deposits, even with the tax deductability on mortgage interest payments. Note households do have incentives to keep some financial assets at hand as home equity is risky and home equity borrowing is not guaranteed. In fact, less than 3 percent of households hold no deposits in our baseline simulation. We use data from the last four periods of the simulations in the tables that follow but results are similar if more periods are included (we use four years of actual data from TransUnion and Equifax).

Because of our modeling choices, moving rates for renters are not meaningful as renters adjust housing services every period so we focus on homeowners who are the ones affected by negative equity to begin with. Table 10 presents unconditional moving rates for homeowners aged 25–60 by house-price appreciation and employment status. The overall moving rate is not affected much by house prices (the rate is 9 percent in periods of house-price appreciation versus 9.2 percent in periods of stable or falling house prices). Regardless of house-price appreciation, the overall moving rate for unemployed owners is more than three times as high as the rate of employed owners (33 percent versus 8 percent).

From now on, we focus on job-related moves to match the empirical analysis (movers who have not received a job offer in a different region are coded as non-movers). The overall moving rate out of the local labor market is 1.6 percent, in the ballpark of the out-of-CBSA and out-of-state moving rates in TransUnion and Equifax. Moving rates for job-related reasons are also significantly higher for unemployed homeowners who are much more responsive to non-local job offers (25.9 percent versus 0.7 percent). These moving rates do not differ much by house appreciation for employed owners but unemployed owners are a bit more likely to accept non-local job offers in periods of house price depreciation (26.7 percent non-local moving rate for unemployed owners who experience house price depreciation versus 25.9 percent in periods of rising house prices).

The previous cross-tabulations are not consistent with a lock-in effect: unemployed homeowners who receive non-local job offers are more likely to accept them than employed owners and housing depreciation does not hinder relocation. This finding could be the result of simulated households not allowing themselves to get into negative equity situations. To explore this further, Table 11 summarizes results from running regressions similar to those performed using TransUnion data in which we take home equity into consideration. Because the model is calibrated to match the median household in the United States, simulated households indeed are less likely to hold negative equity than in the TransUnion sample (4 percent of households in the baseline simulation hold negative equity, 12 percent have low equity and the rest have equity above 20 percent; mean equity is over 60 percent). For these regressions, we interact employment status (employed or unemployed in the previous year) with dummies that classify households in the same four (lagged) equity groups used in the empirical specification (very negative equity, negative equity, 0–20 percent equity and over 20 percent equity). The excluded categories in the regressions are owners in the low but positive equity group. The interpretation of the coefficients for the remaining interactions is moving more or less than these groups. We include age, income, and foreclosure in the last two years as additional controls.

Results from linear regressions, column (1) of Table 11, indicate that unemployed households are much more likely to move while housing equity plays little role. Households with negative or very negative equity move out of the their local market for job reasons (about 31 and 29 percent more likely than the excluded group). Unemployed households with negative equity are slightly more likely to move out of the region than other unemployed households. Households with positive equity have more resources to move out of the region but can also use equity to prop-up nondurable consumption during an unemployment spell, which seems to dominate. Older households are less likely to move (less to gain from a move) and income has no effect on moving, perhaps because job offers are not correlated with income levels in our model. Households who foreclosed in the past are about 4 percentage points more likely to move out of their local market. Results in column (2), which include household fixed effects, are very similar which is not surprising because the households are ex-ante identical in the model (this is unlikely in the data where fixed effects have to be included). From now on, we report results which include individual fixed effects.

Table 12 reports on a regression in which we interact employment status with dummies for housing appreciation and depreciation—this regression gives similar conclusions. Unemployed homeowners do not seem to move less out of the region in periods of housing depreciation. In fact, it is employed households who are slightly less likely to move when house prices depreciate.

Moving and different region types

Although the previous regressions are informative, they are not an exact match to our empirical specification because we do not observe employment status when using credit bureau data. In our empirical specification, we rely on information on local labor market conditions. In our stylized model, we do not keep track of locations *per se* but, among other things, we can change the intensities of local versus non-local job offers to inform our empirical work regarding the relationship between differential employment opportunities across locations, house price growth and moving decisions. This way, we can relate moving decisions to employment conditions in the region as opposed to individual employment status which we do not observe.

We perform an experiment in which we create two types of regions which we label *local strong* and *local weak* regions. The regions differ in the relative intensities of local versus non-local job offers.[29] In local strong regions, 80 percent of the job offers unemployed households receive are local versus 60 percent in the local weak regions. All other parameters are the same as in the baseline calibration. We simulate 54 regions and all regions experience housing depreciation the last three periods of the simulations (those used in the regressions) to mimic the Great Recession. We perform regressions in which we include interactions of region type (local strong or local weak) and dummies that classify households in the four home equity groups previously described, the excluded categories being households with 0–20 percent equity in strong and weak local regions. We also include a dummy variable identifying households who had foreclosed in the previous 24 months.

Table 13, column (1), summarizes the results. Consistent with our findings using TransUnion data, households who live in regions with weak labor markets are more likely to move out of the region regardless of the level of equity. The effect of home equity is non-monotonic in the sense that households with low but positive equity are less likely to move than households with negative equity or higher levels of home equity. The model explains the tendency of people with low equity to be more mobile: people with low equity are more likely to have suffered adverse labor market outcomes which makes the propensity to accept a job in another region higher for the group of individuals with low equity. We know that this explanation must hold, in the model, because we do not observe this pattern in Table 11 which controls for individual level employment status. Households are more likely to move if they have foreclosed in the past. In Column (2), we report regression results when we estimate equity in the simulated data using the same equity estimation procedure utilized in TransUnion data. In column (3), we report regression results when using cumulative house price growth as a proxy for equity which is what we do when using Equifax data. The main conclusions are unchanged, no evidence of a lock-in effect, albeit the coefficients are somewhat different (more people are classified as having very negative equity under both equity estimation procedures). The important point to take from these results is that they are qualitatively similar to those in the TransUnion regressions but using actual employment information in the CBSA, which indicates that our empirical findings using credit bureau data can safely be interpreted as households moving out of CBSAs or states with weak labor markets to take jobs elsewhere and negative home equity not locking them in. If households are moving less during the Great Recession it is not necessarily because home equity is preventing them from moving but because job offers did not arrive at the

[29] We assume that households taking a job in another region think the new region is of the same type as their current region for simplicity but learn what kind of region it is once they have moved.

same rate.

Columns (4)–(6) of Table 13 report regression results from a slightly different experiment in which regions differ in the probability of becoming unemployed rather than in the intensity of local versus non-local job offers. In *local weak* regions, employed workers face a 10 percent probability of becoming unemployed versus a 5 percent probability in *local strong* regions. In this case, households with negative equity, regardless of local market conditions, are more likely to move due to job-related reasons than households with positive equity. Again, no sign of a lock-in effect. Overall, our model, using realistic parameterizations, is able to match the patterns of the TransUnion data well. In the model, the economic incentive from moving in order to accept a job offer outweighs movings costs. The model with the chosen calibration does not match the results of the full Equifax cleaned sample, but we document that this is due to regions with lower concentration of subprime mortgages which are not the regions where lacking out-mobility might impede labor market matching (e.g., Michigan).

5 Conclusion

Using a rich set of data from two of the three major credit bureaus in the United States, combined with property-level home equity measures and mortgage information, we explore when individuals migrate to another CBSA or state. We relate the likelihood of moving to economic conditions in the area of household residence and to the amount of home equity. We conclude that there is no evidence of negative home equity locking households into their local labor market (CBSA or state). A simulated model, where the economic benefits of accepting job offers outweigh the cost of moving, is able to match our empirical findings well.

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Table 1: Descriptive Statistics: TransUnion and Equifax.

	TransUnion		Equifax	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Moved CBSA	2.291	14.962	1.255	11.13
Equity <=–20%	0.050	0.218		
Equity (–20,0)%	0.131	0.338		
Equity [0,20)%	0.333	0.471		
Equity >=20%	0.486	0.500		
Neg. shock to local unemp. rate	0.554	0.497	0.617	0.486
Neg. shock x equity <=–20%	0.045	0.208		
Pos. shock x equity <=–20%	0.005	0.070		
Neg. shock x equity (–20,0)%	0.089	0.285		
Pos. shock x equity (–20,0)%	0.042	0.200		
Neg. shock x equity [0,20)%	0.175	0.380		
Pos. shock x equity [0,20)%	0.157	0.364		
Neg. shock x equity >=20%	0.244	0.429		
Pos. shock x equity >= 20%	0.242	0.428		
Biennial HP gr.<=–20%	0.221	0.415	0.158	0.365
Biennial HP gr. (–20,0)%	0.363	0.481	0.417	0.493
Biennial HP gr. [0,20)%	0.297	0.457	0.327	0.469
Biennial HP gr. >=20%	0.119	0.324	0.097	0.297
Neg. shock x HP gr. <=–20%	0.181	0.385	0.123	0.328
Pos. shock x HP gr. <=–20%	0.039	0.194	0.036	0.185
Neg. shock x HP gr. (–20,0)%	0.201	0.401	0.245	0.430
Pos. shock x HP gr. (–20,0)%	0.163	0.369	0.173	0.378
Neg. shock x HP gr. [0,20)%	0.130	0.336	0.180	0.384
Pos. shock x HP gr. [0,20)%	0.167	0.373	0.147	0.354
Neg. shock x HP gr. >=20%	0.042	0.201	0.070	0.256
Pos. shock x HP gr. >=20%	0.077	0.267	0.027	0.163
Foreclosure dummy	0.070	0.255	0.002	0.047
Credit score	767.4	136.5	731.3	87.26
Subprime score	0.204	0.403	0.186	0.389
Near prime score	0.134	0.341	0.094	0.292
Log per capita inc.	–1.61	0.190	9.883	0.179
Ages below 30, fraction	0.180	0.020	0.181	0.021
Ages above 55, fraction	0.320	0.040	0.323	0.042
Log population	14.83	1.200	14.603	1.261
Mortgage age	0.262	0.180		
Prime mortgage	0.198	0.399		
Subprime mortgage	0.458	0.498		
Alt-A mortgage	0.344	0.475		
Investment purpose	0.028	0.166		
Short-term Hybrid	0.257	0.437		
Neg. shock to local vacancy rate	0.605	0.489		

Note: "Moved CBSA" is a dummy variable that equals 100 if an individual moved to another CBSA within last year. "Neg. shock (to local unemp. rate)" is a dummy variable that equals one if the difference between the annual change in regional unemployment rate and the national average is positive. "Neg. shock to local vacancy rate" is calculated similarly using the vacancy rate instead of unemployment rate. "Foreclosure dummy" for the TransUnion sample equals one if a borrower at time t is in foreclosure (source: CoreLogic). This variable in Equifax sample equals one if a consumer had at least one property in foreclosure during the last 24 months from t. "Credit Score" in TransUnion data is a Vantage Score. In Equifax, this variable is called Risk Score. "Subprime score" and "Near prime" score are dummy variables that equal one if the credit score is less than 641 in TransUnion and less than 661 in Equifax. Prime, Subprime, and Alt-A mortgage are dummy variables that equal one if a mortgage is of a certain risk type, based on the CoreLogic classification. "Mortgage age" is the number of months since mortgage origination. Equity measures were calculated by the authors using loan-to-value ratios at mortgage origination from LoanPerformance adjusted for the subsequent house-price appreciation at the ZIP code level (using house price index from CoreLogic). "Investment purpose" is a dummy variable that equals one if a mortgage was originated primarily for investment purposes. Short-term hybrid is a dummy variable that equals one if a mortgage is 2/28 or 3/27 hybrid. These two variables are form CoreLogic. "Ages below 30" is a fraction of individuals in each CBSA that are younger than 30 years. "Ages above 55" is defined similarly but for individuals older than 55. These variables are from Equifax. All listed variables except for moving rates have been lagged one year for the analysis.

Table 2: Moving Rates in credit bureau data (percent).

Year	**ZIP**	**CBSA**	**State**
Equifax, FRBNY CCP			
2007	4.26	1.40	1.04
2008	3.74	1.32	0.97
2009	3.26	1.05	0.75
Overall	3.75	1.25	0.92
TransUnion			
2007	7.18	2.70	1.76
2008	7.17	2.38	1.43
2009	5.46	1.82	1.14
Overall	6.61	2.29	1.44

Note: The table shows moving rates calculated from the two credit bureaus' datasets. The first column shows the fraction of people who change ZIP codes since the previous year. The second column shows the fraction of people who moved to a different CBSA. The third column shows moving rates to different states. The rates have been multiplied by 100.

Table 3: Correlation matrix. TransUnion. Fixed Effects removed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Moved CBSA	1.000											
(2) Neg. shock x eq. <=–20%	0.045	1.000										
(3) Pos. shock x eq. <=–20%	–0.004	–0.057	1.000									
(4) Neg. shock x eq. (–20,0)%	0.015	–0.174	–0.084	1.000								
(5) Pos. shock x eq. (–20,0)%	–0.020	–0.151	–0.091	–0.168	1.000							
(6) Neg. shock x eq. [0,20)%	0.004	–0.119	–0.044	–0.132	–0.171	1.000						
(7) Pos. shock x eq. [0,20)%	–0.032	–0.176	0.004	–0.263	–0.049	–0.390	1.000					
(8) Neg. shock x eq. >=20%	0.015	0.056	–0.015	–0.003	–0.103	–0.075	–0.261	1.000				
(9) Pos. shock x eq. >=20%	–0.016	–0.103	0.009	–0.161	0.062	–0.288	0.080	–0.683	1.000			
(10) Log per capita inc.	–0.066	–0.160	0.074	–0.118	0.077	–0.104	0.008	0.061	0.139	1.000		
(11) Ages <30, fraction	–0.003	–0.024	0.004	–0.044	0.024	–0.017	0.078	–0.049	0.030	–0.321	1.000	
(12) Ages >55, fraction	0.042	0.087	–0.033	0.105	–0.064	0.079	–0.106	0.037	–0.102	–0.164	–0.679	1.000
(13) Log pop.	–0.074	–0.026	0.008	–0.020	0.010	–0.063	–0.052	0.055	0.065	0.479	–0.047	–0.377
(14) Foreclosed	0.056	0.169	0.010	0.113	–0.011	0.022	–0.109	0.005	–0.093	–0.084	–0.058	0.114
(15) Mortg. age	0.016	–0.022	0.036	–0.021	0.081	–0.037	0.052	–0.022	–0.004	0.115	–0.101	–0.001
(16) Subprime score	0.014	0.065	0.007	0.020	0.054	–0.003	0.068	–0.099	–0.025	–0.240	–0.030	0.132
(17) Near prime score	0.002	–0.021	–0.009	–0.010	0.012	0.012	0.064	–0.052	0.002	–0.151	0.014	0.062
(18) Log score	–0.024	–0.062	0.006	–0.024	–0.071	–0.016	–0.140	0.172	0.036	0.499	–0.009	–0.231
(19) Equity<=–20%	0.042	0.946	0.271	–0.196	–0.175	–0.129	–0.168	0.049	–0.097	–0.130	–0.022	0.074
(20) Equity (–20,0)%	0.002	–0.248	–0.131	0.812	0.440	–0.221	–0.269	–0.064	–0.109	–0.062	–0.026	0.058
(21) Neg. shock	0.036	0.226	–0.098	0.325	–0.312	0.483	–0.615	0.663	–0.769	–0.135	–0.074	0.156
(22) HP gr. <=–20%	0.020	0.395	0.085	0.282	–0.056	0.066	–0.242	0.033	–0.268	–0.044	–0.088	0.114
(23) HP gr. (–20,0)%	–0.022	–0.217	–0.046	–0.047	0.125	0.077	0.106	0.011	–0.075	0.066	–0.014	–0.024
(24) HP gr. [0,20)%	–0.010	–0.085	–0.006	–0.144	–0.046	–0.075	0.107	–0.032	0.173	0.029	0.079	–0.121
(25) HP gr. $\geq$ 20%	0.024	–0.020	–0.023	–0.067	–0.064	–0.095	–0.023	–0.011	0.203	–0.092	0.018	0.070

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(14) Foreclosed	–0.011	1.000										
(15) Mortg. age	0.045	–0.008	1.000									
(16) Subprime score	–0.124	0.088	0.127	1.000								
(17) Near prime score	–0.087	–0.006	0.007	–0.355	1.000							
(18) Log score	0.256	–0.099	–0.086	–0.686	–0.176	1.000						
(19) Equity<=–20%	–0.022	0.166	–0.009	0.065	–0.023	–0.058	1.000					
(20) Equity (–20,0)%	–0.012	0.096	0.029	0.050	–0.002	–0.064	–0.282	1.000				
(21) Neg. shock	–0.020	0.130	–0.056	–0.039	–0.041	0.076	0.186	0.111	1.000			
(22) HP gr. <=–20%	0.077	0.169	0.117	–0.023	–0.056	0.082	0.409	0.224	0.334	1.000		
(23) HP gr. (–20,0)%	–0.047	–0.031	0.203	0.068	0.019	–0.077	–0.225	0.032	–0.041	–0.519	1.000	
(24) HP gr. [0,20)%	0.016	–0.081	–0.110	0.015	0.026	–0.034	–0.084	–0.158	–0.168	–0.216	–0.505	1.000
(25) HP gr. $\geq$ 20%	–0.043	–0.044	–0.308	–0.102	0.002	0.069	–0.027	–0.099	–0.107	–0.100	–0.224	–0.364

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

	CBSA		State	
Neg. shock × equity$_{<=-20\%}$	0.65***	0.90***	0.23***	0.37***
	(9.48)	(13.02)	(5.11)	(8.28)
Pos. shock × equity$_{<=-20\%}$	0.34**	0.52***	0.34**	0.51***
	(2.51)	(3.82)	(2.03)	(3.06)
Neg. shock × equity$_{(-20,0]\%}$	0.05	0.22***	0.02	0.14***
	(1.12)	(5.18)	(0.75)	(4.65)
Pos. shock × equity$_{(-20,0]\%}$	–0.06	0.18***	–0.06	0.12**
	(1.02)	(3.14)	(1.14)	(2.44)
Neg. shock × equity$_{[0,20)\%}$	excluded group	excluded group	excluded group	excluded group
Pos. shock × equity$_{[0,20)\%}$	excluded group	excluded group	excluded group	excluded group
Neg. shock × equity$_{>=20\%}$	0.62***	–0.01	0.36***	–0.05*
	(16.75)	(0.15)	(13.13)	(1.78)
Pos. shock × equity$_{>=20\%}$	0.92***	0.13***	0.61***	0.09***
	(21.24)	(2.94)	(17.85)	(2.60)
Foreclosure dummy		2.01***		1.28***
		(33.66)		(28.77)
Mortgage age		17.43***		11.98***
		(82.69)		(72.42)
Log score		–1.38***		–0.37***
		(7.41)		(2.60)
Subprime score		0.27***		0.17***
		(4.75)		(3.78)
Near prime score		0.11***		0.05
		(2.60)		(1.45)
CBSA x year effects	Y	Y	N	N
State x year effects	N	N	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	3,115,931	3,115,931	3,292,771	3,292,771
No. indiv.	1,507,652	1,507,652	1,592,451	1,592,451

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

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

	No invest.	No invest. nor Hybrid	Subprime	Subprime score	Alt-A	Prime
Neg. shock × equity$_{<=-20\%}$	0.91***	1.08***	1.03***	0.87***	1.05***	0.83***
	(12.99)	(13.31)	(10.53)	(5.18)	(9.14)	(3.99)
Pos. shock × equity$_{<=-20\%}$	0.53***	0.79***	0.45**	0.63**	0.43**	1.59***
	(3.86)	(4.91)	(2.30)	(2.07)	(1.96)	(3.31)
Neg. shock × equity$_{(-20,0]\%}$	0.22***	0.31***	0.25***	0.21**	0.23***	0.59***
	(5.15)	(6.20)	(4.22)	(2.15)	(3.20)	(4.91)
Pos. shock × equity$_{(-20,0]\%}$	0.19***	0.35***	0.22***	0.21*	0.09	0.73***
	(3.26)	(4.96)	(3.05)	(1.90)	(0.90)	(3.43)
Neg. shock × equity$_{[0,20)\%}$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Pos. shock × equity$_{[0,20)\%}$	excluded group	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock × equity$_{>=20\%}$	–0.01	–0.04	–0.02	–0.15*	0.04	–0.39***
	(0.32)	(0.85)	(0.34)	(1.74)	(0.55)	(4.50)
Pos. shock × equity$_{>=20\%}$	0.11**	0.04	0.09	0.00	0.19**	–0.08
	(2.54)	(0.70)	(1.55)	(0.01)	(2.40)	(0.63)
Foreclosure dummy	2.02***	2.09***	1.75***	1.22***	2.45***	2.56***
	(33.32)	(23.98)	(25.39)	(13.18)	(20.26)	(7.43)
Mortgage age	17.37***	19.35***	13.41***	10.43***	26.89***	25.15***
	(81.45)	(78.85)	(49.60)	(28.70)	(61.39)	(50.55)
Log score	–1.49***	–0.58***	–2.14***	–3.78***	–0.29	–0.05
	(7.92)	(2.71)	(8.16)	(10.02)	(0.91)	(0.12)
Subprime score	0.25***	0.37***	–0.02	–1.24***	0.68***	0.74***
	(4.29)	(5.27)	(0.32)	(9.33)	(5.64)	(2.62)
Near prime score	0.10**	0.16***	–0.05	–0.33***	0.17**	–0.31
	(2.52)	(3.16)	(0.94)	(2.68)	(2.12)	(1.50)
CBSA x year effects	Y	Y	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y	Y	Y
No. obs.	3,026,363	2,239,927	1,426,438	520,526	1,071,348	618,145
No. indiv.	1,466,248	1,058,128	732,816	275,375	523,920	280,278

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

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

	Non-recourse states	All states, vacancy rates	All states, empl. growth
Neg. shock × equity$_{<=-20\%}$	0.87***	0.91***	0.82***
	(10.02)	(11.08)	(11.27)
Pos. shock × equity$_{<=-20\%}$	1.48***	0.77***	0.40***
	(3.56)	(8.64)	(3.28)
Neg. shock × equity$_{(-20,0]\%}$	0.20***	0.19***	0.20***
	(3.34)	(3.82)	(4.66)
Pos. shock × equity$_{(-20,0]\%}$	0.28**	0.24***	0.17***
	(1.96)	(5.16)	(2.93)
Neg. shock × equity$_{[0,20)\%}$	excluded group	excluded group	excluded group
Pos. shock × equity$_{[0,20)\%}$	excluded group	excluded group	excluded group
Neg. shock × equity$_{>=20\%}$	–0.10**	–0.04	–0.03
	(1.98)	(1.01)	(0.83)
Pos. shock × equity$_{>=20\%}$	0.42***	0.11***	0.01
	(5.14)	(2.72)	(0.24)
Foreclosure dummy	2.02***	2.01***	1.65***
	(22.12)	(33.75)	(26.84)
Mortgage age	16.74***	17.43***	15.40***
	(53.36)	(82.68)	(70.45)
Log score	–1.45***	–1.38***	–1.02***
	(5.05)	(7.43)	(5.23)
Subprime score	0.51***	0.28***	0.25***
	(5.22)	(4.78)	(4.18)
Near prime score	0.21***	0.11***	0.12***
	(2.89)	(2.63)	(2.71)
CBSA x year effects	Y	Y	Y
Individual effects	Y	Y	Y
No. obs.	1,328,650	3,115,931	2,485,123
No. indiv.	639,511	1,507,652	1,199,072

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

Table 7: TransUnion, years 2007–2009.
Probability of moving to another CBSA. House prices.

	Biennial HP gr.	Cumulative HP gr.
Neg. shock × HP gr.$<= -20\%$	–0.05	0.46***
	(0.64)	(7.14)
Pos. shock × HP gr.$<= -20\%$	–0.06	0.25**
	(0.72)	(2.12)
Neg. shock × HP gr.$(-20, 0)\%$	0.01	0.03
	(0.23)	(0.93)
Pos. shock × HP gr.$(-20, 0)\%$	–0.04	0.12***
	(0.90)	(2.97)
Pos. shock × HP gr. $[0, 20)\%$	excluded group	excluded group
Pos. shock × HP gr. $[0, 20)\%$	excluded group	excluded group
Neg. shock × HP gr.$>= 20\%$	0.07	0.06
	(0.85)	(1.21)
Neg. shock × HP gr.$>= 20\%$	–0.04	0.00
	(0.54)	(0.05)
Foreclosure dummy	2.07***	2.05***
	(34.86)	(34.39)
Subprime score	0.30***	0.29***
	(5.24)	(5.07)
Near prime score	0.11***	0.11***
	(2.77)	(2.71)
Mortgage age	17.33***	17.48***
	(84.52)	(79.12)
Log score	–1.51***	–1.44***
	(8.11)	(7.74)
CBSA x year effects	Y	Y
Individual effects	Y	Y
No. obs.	3,112,228	3,112,228
No. indiv.	1,506,682	1,506,682

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_t + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment growth in a CBSA. The four dummy variables for house price growth ("HP gr.") are measured using lagged biennial growth of house prices in a ZIP code (second column) or lagged house price appreciation since mortgage origination (third column). $\delta_j \times \mu_t$ are (lagged) CBSA x year fixed effects, and ν_i are individual fixed effects. Robust standard errors are clustered by individual. *** (**) [*] significant at the 1 (5) [10]% level.

Table 8: Equifax, years 2007-2009. Probability of moving to another CBSA.

	Orig. year > 1999	Orig. year > 2005	Balance $\geq 95\%$	Subprime ZIP codes
Neg. shock (cty/st) $\times$ HP gr.$_{<-20\%}$	–0.06	1.27***	–0.02	0.22*
	(0.88)	(9.77)	(0.14)	(1.76)
Pos. shock (cty/st) $\times$ HP gr.$_{<-20\%}$	–0.00	1.51***	–0.11	–0.55
	(0.03)	(5.94)	(0.54)	(0.93)
Neg. shock (cty/st) $\times$ HP gr.$_{(-20,0]\%}$	–0.05	0.56***	–0.02	0.14
	(1.53)	(8.23)	(0.43)	(1.60)
Pos. shock (cty/st) $\times$ HP gr.$_{(-20,0]\%}$	–0.09**	0.69***	–0.16***	–0.01
	(2.48)	(9.71)	(2.67)	(0.05)
Neg. shock (cty/st) $\times$ HP gr.$_{\geq 20\%}$	excluded group	excluded group	excluded group	excluded group
Pos. shock (cty/st) $\times$ HP gr.$_{\geq 20\%}$	excluded group	excluded group	excluded group	excluded group
Neg. shock (cty/st) $\times$ HP gr.$_{>20\%}$	–0.12**	–0.25	–0.35***	–0.19*
	(3.20)	(1.40)	(3.84)	(1.79)
Pos. shock (cty/st) $\times$ HP gr.$_{>20\%}$	–0.07*	0.36**	–0.25***	–0.15
	(1.79)	(2.24)	(3.08)	(1.01)
Foreclosure dummy	1.65**	1.76***	1.48***	1.85***
	(13.03)	(9.91)	(10.69)	(7.23)
Mortgage age/100	0.05**	0.04***	0.01	0.02***
	(52.74)	(22.61)	(0.14)	(7.11)
Subprime score	–0.05	–0.12	–0.02	0.39***
	(1.06)	(1.34)	(0.31)	(2.79)
Near prime score	–0.07*	–0.14*	0.06***	0.20*
	(1.75)	(1.86)	(38.38)	(1.80)
CBSA x year effects	Y	Y	Y	Y
Individual effects	Y	Y	Y	Y
No. obs.	3,229,907	1,106,616	1,702,341	289,103
No. indiv.	1,419,205	612,839	944,760	119,221

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_t + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. Pos./Neg. shock are dummy variables that capture positive and negative shocks to unemployment growth in a CBSA. The four dummy variables for house price growth ("HP gr.") are measured using lagged house price appreciation since mortgage origination. See Section 3.2 for the detailed variable description. $\delta_j \times \mu_t$ are (lagged) CBSA x year fixed effects, and ν_i are individual fixed effects. Robust standard errors are clustered by individual. *** (**) [*] significant at the 1 (5) [10]% level. For the results reported in column"Orig. year > 1999" we used the Equifax sample of homeowners that have at most one first-lien mortgage originated after year 1999. Sample for "Orig. year > 2005" restricts origination year to be > 2005. "Balance ≥ 95%" restricts the sample of mortgages with (lagged) balance-to-loan ratio ≥ 95%. "Subprime ZIP codes" restricts the sample to ZIP codes with the ratio of loans reported in TransUnion relative to those in Equifax exceeding the 90th percentile.

Table 9: Benchmark Calibration Parameters.

Preferences		
	Cobb-Douglas utility; .22 weight for housing.	
	Discount rate 3.99%; 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% replacement rate.	
		Local job offer probability 66.5%.
		Elsewhere job offer probability 28.5%, no permanent income increase.
		No job offer probability 5%.
	Employed:	
		Unemployment shock probability 5%.
		Elsewhere job offer probability 5%, 10% permanent income increase.
		No change probability, 90%.
	Pension: 50% of last working period permanent income.	
Interest rates		
	4% for deposits; 4.5% for mortgages.	
	No uncertainty.	
Housing Market		
	Down payment 5%.	
	Buying (selling) cost 2% (8%). Additional 1% selling cost for non-local moves.	
	Foreclosure: income (house) one-time cost 20% (8%).	
Taxes		
	Proportional taxation.	
	Income tax rate 20% (TAXSIM); mortgage interest fully deductible.	
House Prices		
	Average real appreciation 0; variance 0.0131.	
	Housing depreciation: owners, 1.5%; renters, 2.2%	
	Rent-to-price ratio 6.9%.	
Other		
	No income and house-price correlation.	
	Warm-glow bequest motive.	

Table 10: Unconditional Moving Rates in the Model. Owners, Aged 25–60.

House Price Growth	All	Employed	Unemployed
	All moves		
HP growth $_{\leq 0\%}$	0.092	0.081	0.334
HP growth $_{>0\%}$	0.090	0.079	0.327
Total	0.092	0.080	0.331
	Job-related moves		
HP growth $_{\leq 0\%}$	0.016	0.007	0.267
HP growth $_{>0\%}$	0.016	0.007	0.244
Total	0.016	0.007	0.259

Table 11: Moving in the Model. Equity.
Owners, Aged 25–60.

	OLS (1)	Fixed Effects (2)
Unemployed × Equity $_{\leq -20}$%	31.48***	20.84**
	(3.34)	(2.04)
Employed × Equity $_{\leq -20}$%	0.54	1.11
	(0.51)	(0.86)
Unemployed × Equity $_{(-20,0)}$%	28.58***	24.67***
	(8.71)	(7.33)
Employed × Equity $_{(-20,0)}$%	–0.98***	–0.30
	(4.75)	(1.16)
Unemployed × Equity $_{[0,20)}$%	excluded group	excluded group
Employed × Equity $_{[0,20)}$%	excluded group	excluded group
Unemployed × Equity $_{\geq 20}$%	25.57***	22.60***
	(46.85)	(40.90)
Employed × Equity $_{\geq 20}$%	–0.69***	–0.33*
	(6.65)	(1.78)
Age	–0.18***	
	(3.21)	
Age square/100	0.17***	
	(2.97)	
Log income	–0.06	–0.19**
	(1.36)	(2.19)
Foreclosed (past 24 months)	4.20***	5.09***
	(7.60)	(8.04)
Region x year effects	Y	Y
N	169,875	169,875

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_t + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, X is a vector of (lagged) regressors, $\delta_j \times \mu_t$ is the product of (lagged) region fixed effects and time fixed effects and ν_i are individual fixed effects. Robust standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10]% level. Note in column (1) $\nu_i = \nu$.

Table 12: Moving in the Model. Appreciation-Depreciation. Owners, Aged 25–60.

Unemployed × HP growth $_{\leq 0}$	26.83***
	(42.66)
Unemployed × HP growth $_{>0}$	25.33***
	(28.98)
Employed × HP growth $_{\leq 0}$	–0.16***
	(4.38)
Employed × HP growth $_{>0}$	excluded group
Age	–0.19***
	(3.36)
Age square/100	0.18***
	(3.18)
Log income	0.03
	(0.56)
Foreclosed (past 24 months)	4.33***
	(7.92)
N	169,875

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = \alpha + X_{it-1}\beta + u_{it}$, 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. *** (**) [*] significant at the 1 (5) [10]% level. Standard errors are clustered by individual.

Table 13: Moving in the Model. Equity and Different Region Types. Owners, Aged 25–60.

	Diff. Local Offers			Diff. Unemp. Rate		
	Actual equity	Estimated equity	Cumulative HP gr.	Actual equity	Estimated equity	Cumulative HP gr.
	(1)	(2)	(3)	(4)	(5)	(6)
Local Weak × equity $_{\leq -20}$%	2.95***	4.19***	4.03***	2.21***	3.38***	3.28***
	(3.45)	(13.84)	(15.55)	(2.78)	(12.18)	(13.94)
Local Strong × equity $_{\leq -20}$%	1.47**	2.60***	2.52***	2.47***	3.33***	3.33***
	(1.99)	(10.51)	(12.14)	(3.07)	(14.14)	(14.13)
Local Weak × equity $_{(-20,0)}$%	1.55***	1.83***	0.51***	1.11***	1.47***	0.32**
	(5.33)	(9.64)	(2.91)	(4.08)	(8.55)	(2.05)
Local Strong × equity $_{(-20,0)}$%	0.52**	1.16***	0.24*	1.29***	0.39**	0.39**
	(2.16)	(7.43)	(1.75)	(4.65)	(2.50)	(2.51)
Local Weak × equity $_{[0,20)}$%	excluded category	excluded category	excluded category	excluded category	excluded category	excluded category
Local Strong × equity $_{[0,20)}$%	excluded category	excluded category	excluded category	excluded category	excluded category	excluded category
Local Weak × equity $_{\geq 20}$%	0.63***	–1.53***	–0.33	0.62***	–1.56***	–0.38*
	(2.72)	(4.21)	(1.44)	(2.89)	(4.73)	(1.80)
Local Strong × equity $_{\geq 20}$%	0.57***	–0.86***	0.05	0.63***	–0.29	–0.29
	(2.95)	(3.12)	(0.31)	(2.95)	(1.37)	(1.39)
Foreclosed (past 24 months)	3.76***	3.43***	3.72***	3.63***	3.52***	3.65***
	(14.14)	(13.89)	(15.36)	(13.50)	(14.34)	(15.04)
Region x year effects	Y	Y	Y	Y	Y	Y
N	333567	333,567	333,567	332,952	332,952	332,952

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j \times \mu_t + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, X is a vector of (lagged) regressors, $\delta_j \times \mu_t$ is the product of (lagged) region fixed effects and time fixed effects and ν_i are individual fixed effects. Robust standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10]% level. We simulate two kinds of differences between regions: in the first two columns, weak local regions and strong local regions differ in the intensity of local versus non-local job offers (60 percent and 80 percent, respectively) and, in the last two columns, weak local regions and strong local regions differ in the probability of becoming unemployed (10 percent and 5 percent, respectively).

Figure 1: Distribution of Negative Equity by State.

(Percentage of individuals with negative equity in TransUnion. Categories are $< 1\%$, 1-5%, 5-20%, 40-50%, $> 50\%$)

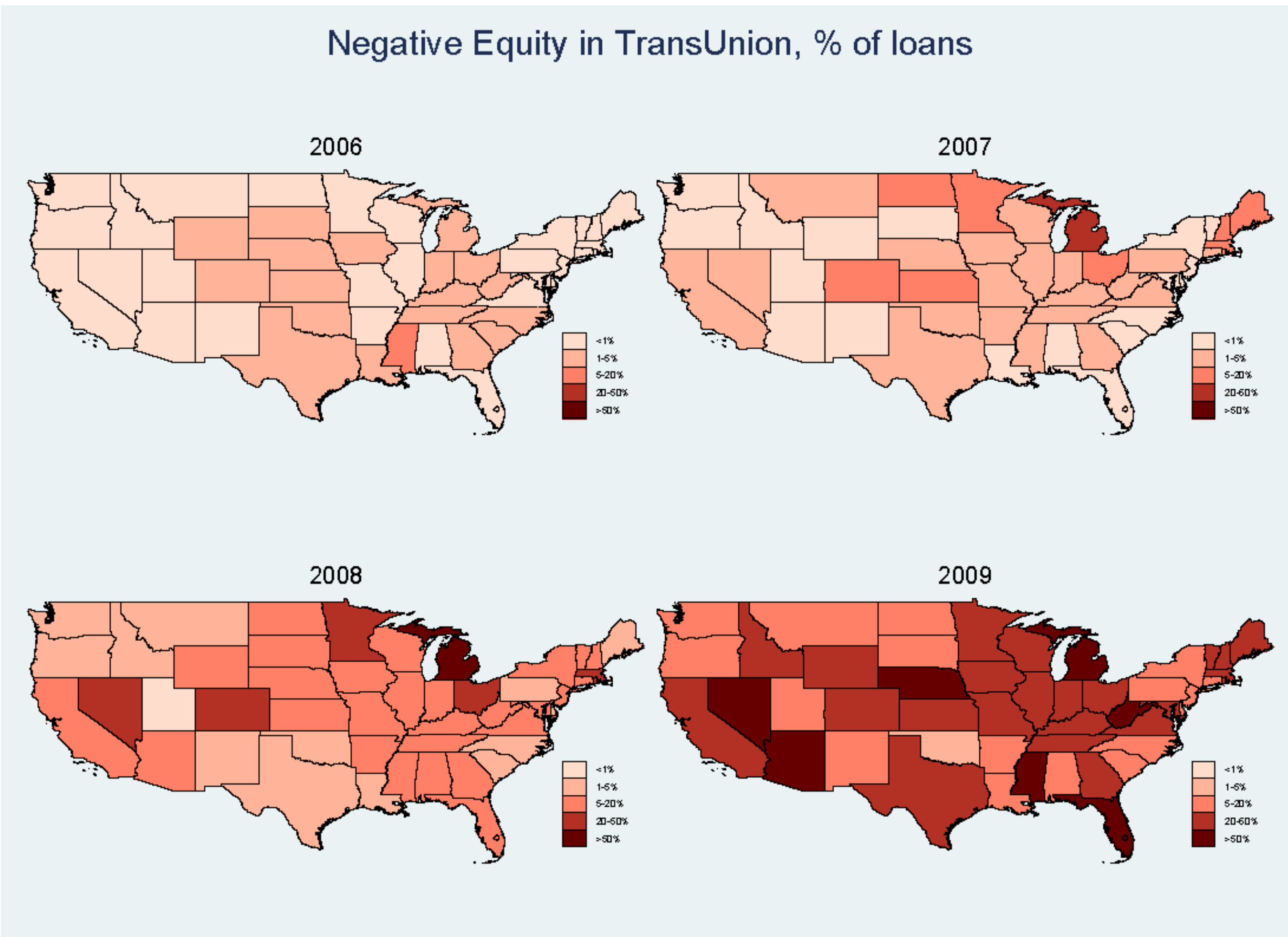
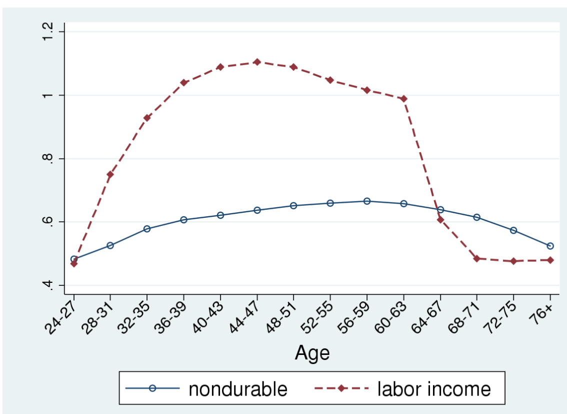
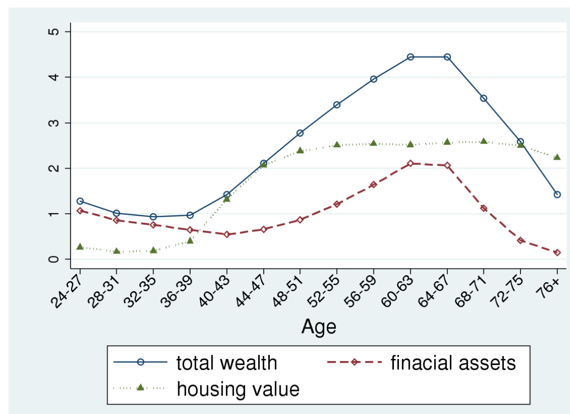


Figure 2: Life-cycle Profiles. The Benchmark Case.

(Data for moving rates and foreclosures by age cohort are from Equifax, FRBNY CCP)



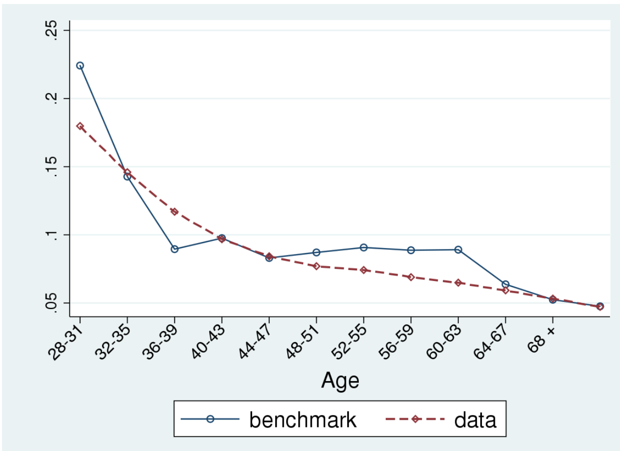
(a) Income and Consumption



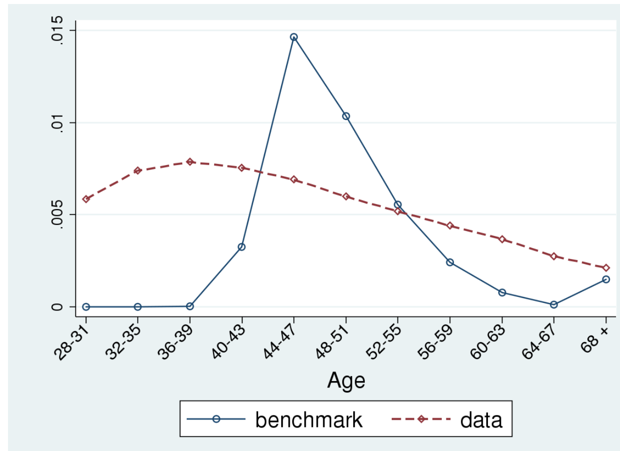
(b) Wealth

Figure 3: The Benchmark and the Data.

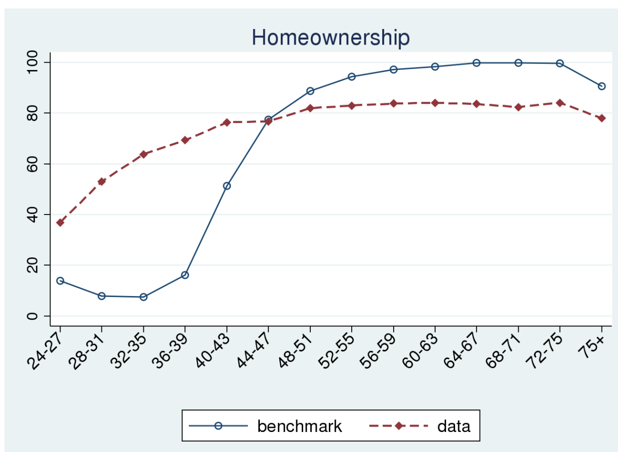
(Data for homeownership, wealth and earnings from the Survey of Consumer Finances, averages from 1989–2004. Data on moving rates and foreclosure from Equifax)



(a) Overall moving rates



(b) Foreclosure rate (out of total households)



(c) Homeownership

(d) Wealth and Earnings

A Appendix

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

In Table A.2, we display regressions where the dependent variable is local moves between ZIP codes (staying in the same CBSA) or between counties (staying in the same state). Local moves are not the focus of this article but it is reassuring that the main qualitative patterns remain also for such moves which likely are partly driven by a desire to upgrade or downgrade housing but are also partly job-related—see, e.g., Table 6 in Ferreira et al. (2011).

Table A.3 shows the results of our main specification when individual fixed effects are not included. The patterns are similar to the results of Table 4 which properly, we argue, includes individual fixed effects. The lower mobility of individuals with very negative equity is less pronounced. This mechanically implies that the omitted fixed effects are correlated with negative equity. People, who throughout the sample have highly negative equity, will impact on the regressions without fixed effects but not on those with fixed effects, so the lower coefficients are likely to reflect that people with permanent negative equity are less mobile than people who were forced into this category by collapsing house prices. The coefficient for individuals with high positive equity changes sign to negative from positive in Table 4. This means that individuals with permanently high positive equity are less likely to move, maybe reflecting that they are older, while individuals who move from other categories into this equity position are more likely to move.

The coefficient to average age over 55 (in the location) also changes sign to become positive and significant when individual fixed effects are not included. We conjecture that the coefficient now picks up that the individual in the sample is more likely to be older (a feature that the individual fixed effect controls for) and that people over 55 are more likely to migrate to retirement communities. One could also notice that financial score becomes highly significant with a positive coefficient, maybe reflecting that more educated individuals are more mobile and also have higher scores. The point of these remarks is not so much that the offered conjectures are likely to be correct but rather that regressions without fixed effects capture cross-sectional patterns, whatever they are, and that such regressions may be misleading for examining non-cross-sectional questions such as the one studied in the present paper; namely, whether housing equity constrains mobility in regions that are hit by labor market shocks.

Table A.1: Correlation matrix. Fixed Effects not removed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Moved CBSA	1.000											
(2) Neg. shock x eq. ≤–20%	0.012	1.000										
(3) Pos. shock x eq. ≤–20%	–0.002	–0.015	1.000									
(4) Neg. shock x eq. (–20,0)%	0.015	–0.068	–0.022	1.000								
(5) Pos. shock x eq. (–20,0)%	–0.001	–0.046	–0.015	–0.066	1.000							
(6) Neg. shock x eq. [0,20)%	0.012	–0.101	–0.032	–0.145	–0.096	1.000						
(7) Pos. shock x eq. [0,20)%	0.002	–0.094	–0.030	–0.135	–0.090	–0.199	1.000					
(8) Neg. shock x eq. ≥20%	–0.013	–0.124	–0.040	–0.178	–0.119	–0.262	–0.245	1.000				
(9) Pos. shock x eq. ≥20%	–0.015	–0.123	–0.040	–0.177	–0.118	–0.261	–0.244	–0.321	1.000			
(10) Log per capita inc.	–0.033	–0.137	0.051	–0.094	0.050	–0.077	0.010	0.049	0.109	1.000		
(11) Ages <30, fraction	0.000	–0.041	–0.005	–0.045	0.005	–0.011	0.057	–0.026	0.035	–0.314	1.000	
(12) Ages >55, fraction	0.019	0.100	–0.012	0.100	–0.025	0.059	–0.078	0.012	–0.101	–0.168	–0.681	1.000
(13) Log pop.	–0.038	–0.023	0.005	–0.017	0.006	–0.048	–0.036	0.041	0.051	0.479	–0.045	–0.375
(14) Foreclosed	0.051	0.144	0.020	0.139	0.045	0.060	–0.002	–0.110	–0.128	–0.052	–0.040	0.079
(15) Mortg. age	–0.028	0.013	0.015	–0.060	–0.035	–0.126	–0.136	0.163	0.111	0.022	–0.060	0.046
(16) Subprime score	–0.004	0.073	0.020	0.054	0.060	0.027	0.059	–0.104	–0.073	–0.128	–0.023	0.080
(17) Near prime score	–0.002	0.005	0.004	0.017	0.028	0.022	0.060	–0.062	–0.035	–0.094	0.011	0.035
(18) Log score	0.000	–0.096	–0.027	–0.091	–0.094	–0.066	–0.127	0.193	0.129	0.237	0.000	–0.115
(19) Equity≤–20%	0.011	0.948	0.305	–0.072	–0.048	–0.106	–0.099	–0.131	–0.130	–0.114	–0.040	0.091
(20) Equity (–20,0)%	0.012	–0.085	–0.027	0.806	0.538	–0.179	–0.168	–0.221	–0.220	–0.050	–0.035	0.070
(21) Neg. shock	0.012	0.195	–0.078	0.281	–0.233	0.414	–0.482	0.510	–0.630	–0.128	–0.074	0.155
(22) HP gr. ≤–20%	–0.009	0.408	0.130	0.253	0.049	0.029	–0.149	–0.059	–0.250	–0.066	–0.116	0.162
(23) HP gr. (–20,0)%	–0.008	–0.163	–0.052	0.002	0.091	0.076	0.071	0.009	–0.093	0.065	–0.014	0.000
(24) HP gr. [0,20)%	0.001	–0.141	–0.045	–0.153	–0.093	–0.048	0.063	0.036	0.175	0.039	0.096	–0.149
(25) HP gr. ≥ 20%	0.021	–0.080	–0.026	–0.110	–0.067	–0.080	–0.004	0.012	0.211	–0.067	0.034	0.002

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(14) Foreclosed	–0.007	1.000										
(15) Mortg. age	0.011	–0.058	1.000									
(16) Subprime score	–0.066	0.229	0.020	1.000								
(17) Near prime score	–0.054	0.021	–0.059	–0.199	1.000							
(18) Log score	0.121	–0.255	0.089	–0.745	–0.254	1.000						
(19) Equity≤–20%	–0.020	0.144	0.017	0.076	0.006	–0.100	1.000					
(20) Equity (–20,0)%	–0.011	0.144	–0.071	0.081	0.030	–0.132	–0.089	1.000				
(21) Neg. shock	–0.021	0.091	0.016	–0.007	–0.026	0.024	0.161	0.100	1.000			
(22) HP gr. ≤–20%	0.047	0.117	0.189	0.045	–0.033	–0.018	0.430	0.243	0.286	1.000		
(23) HP gr. (–20,0)%	–0.039	0.012	0.087	0.033	–0.001	–0.017	–0.172	0.056	–0.002	–0.402	1.000	
(24) HP gr. [0,20)%	0.017	–0.071	–0.135	–0.032	0.016	0.025	–0.149	–0.185	–0.153	–0.345	–0.491	1.000
(25) HP gr. ≥ 20%	–0.028	–0.068	–0.181	–0.061	0.022	0.013	–0.085	–0.133	–0.148	–0.196	–0.278	–0.239

Table A.2: TransUnion, years 2007–2009. Probability of local moves.

	ZIP, not CBSA	Cty, not state
Neg. shock × equity$_{\leq -20\%}$	3.67***	1.74***
	(37.25)	(21.72)
Pos. shock × equity$_{\leq -20\%}$	2.87***	0.72***
	(11.38)	(11.95)
Neg. shock × equity$_{(-20,0)\%}$	1.24***	0.47***
	(17.81)	(10.58)
Pos. shock × equity$_{(-20,0)\%}$	0.69***	0.25***
	(7.72)	(6.29)
Neg. shock × equity$_{[0,20)\%}$	0.48***	0.02
	(9.57)	(0.59)
Pos. shock × equity$_{[0,20)\%}$	excluded group	excluded group
Neg. shock × equity$_{\geq 20\%}$	0.60***	0.16***
	(10.02)	(4.70)
Pos. shock × equity$_{\geq 20\%}$	0.51***	0.08**
	(8.32)	(2.56)
Log per capita inc.	–1.06	2.11***
	(0.91)	(4.37)
Ages below 30, fraction	17.26***	2.06
	(6.66)	(0.53)
Ages above 55, fraction	–8.61**	21.36***
	(2.47)	(5.78)
Log population	9.12***	9.35***
	(8.93)	(11.23)
Foreclosure dummy	3.11***	1.40***
	(32.82)	(24.53)
Mortgage age	17.58***	7.05***
	(45.00)	(29.82)
Subprime score	0.57***	0.13**
	(6.61)	(2.56)
Near prime score	–0.00	0.02
	(0.02)	(0.62)
Log score	–5.43***	–1.73***
	(19.81)	(10.31)
Time effects	Y	Y
County effects	N	Y
CBSA effects	Y	N
Individual effects	Y	Y
N	3,059,905	3,222,682

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j + \mu_t + \nu_i + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors; δ_j is (lagged) county or CBSA (in the first column) fixed effects, μ_t and ν_i are time and individual fixed effects, respectively. Robust standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10]% level.

Table A.3: TransUnion, years 2007–2009. Moving CBSA. No Individual Fixed Effects.

	(1)	(2)
Neg. shock × equity$\leq -20\%$	0.59***	0.28***
	(10.09)	(4.75)
Pos. shock × equity$\leq -20\%$	0.34***	0.26**
	(3.04)	(2.27)
Neg. shock × equity$(-20, 0]\%$	0.52***	0.30***
	(11.72)	(6.79)
Pos. shock × equity$(-20, 0]\%$	0.34***	0.24***
	(7.10)	(5.15)
Neg. shock × equity$[0, 20]\%$	0.02	–0.05
	(0.45)	(1.37)
Pos. shock × equity$_{[0,20)\%}$	excluded	excluded
	group	group
Neg. shock × equity$\geq$ 20%	–0.83***	–0.73***
	(26.55)	(22.63)
Pos. shock × equity$\geq$ 20%	–0.69***	–0.60***
	(25.17)	(21.07)
Log per capita inc.	9.09***	9.15***
	(11.75)	(11.84)
Ages below 30, fraction	–7.88	–9.02
	(0.93)	(1.06)
Ages above 55, fraction	18.09**	33.41***
	(2.47)	(4.57)
Log population	–0.97	–0.53
	(0.82)	(0.44)
Foreclosure dummy		2.95***
		(59.20)
Mortgage age		–0.45***
		(9.95)
Subprime score		–0.10**
		(2.39)
Near prime score		–0.15***
		(4.71)
Log score		1.66***
		(17.54)
Time effects	Y	Y
CBSA effects	Y	Y
Individual effects	N	N
N	3115931	3115931

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = X_{it-1}\beta + \delta_j + \mu_t + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors; δ_j is (lagged) CBSA fixed effects, μ_t is time fixed effects. Robust standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10]% level.