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 (from addresses and new mortgages) with high certainty whether and where households move. 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 people with negative equity in their homes move less when employment growth is high but move more when it is low—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 their homes which, 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 hard to come by. Using credit report data, we provide evidence that labor market adjustment in the United States is not significantly hampered by households with negative home equity being unable to move to better job prospects.

We use data from two leading credit bureaus in the United States. We obtained one 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. The other dataset is from TransUnion and contains credit information for borrowers with non-agency securitized mortgages. This dataset 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 to analyze the underlying collateral of non-agency mortgage-backed securities.

For each loan in the LP dataset, we observe most of the underwriting criteria measured at the time of loan origination: FICO 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 state), the mortgage rate at origination and thereafter, 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

[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 whose balances are 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.

subsequent house price changes in the area (ZIP code). For brevity, thereafter we will label the two datasets described above as Equifax and TransUnion, 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 (from addresses and new mortgages) whether households move. We merge these datasets with labor market data at the county and state levels from the Bureau of Labor Statistics and 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 low home equity. We find no evidence of a lock-in effect. While borrowers with negative equity move less locally (possibly to avoid realizing losses) when employment growth is negative, they are more likely to move out of state than other borrowers, suggesting that the opportunity to get a (better) job dominates considerations related to housing equity when local employment opportunities are scarce.

We provide a brief overview of the pertinent literature. Oswald (1997) suggests that homeownership may impact on labor market clearing because high costs of selling and buying houses may 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. Green & Hendershott (2001) confirm this result, although they find that only prime aged individuals of aged 35–64 are subject to lock-in. Guler & Taskin (2011) document, using data for U.S. Metropolitan Statistical Areas (MSAs), that homeownership is positively correlated with unemployment rates but only when local labor conditions are weak. They build a model that shows how homeownership can lead to higher unemployment rates in distressed labor markets. 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.[3] 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. MSAs and in U.S. 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

[3]Earlier studies using U.S. data such as Coulson & Fischer (2002) did not find support for the Oswald hypothesis but their work criticized for not controlling for selectivity bias as households who are less mobile to begin with self-select into homeownership).

industry/geography cells) labor market conditions play a significant role in matching. Barnichon, Elsby, Hobijn & Sahin (2011) find that the drop in matching efficiency was particularly pronounced in construction, transportation, trade, and utilities. It is well known that the collapse in house prices and construction during the crisis was particularly pronounced in the states of Florida, Nevada, Arizona, and California. 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. Schmitt & Warner (2011), using the Displaced Workers Survey, confirms 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.

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 for 2007–2009 to show that there is a lock-in effect for homeowners who live in areas with large house price declines which presumably limit geographic mobility because many homes in such areas have negative equity. The authors, however, find that this 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, the study concludes 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 (2010) 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 correlated with higher unemployment in weak local labor markets but not in strong labor markets. Guler & Taskin (2011) build a model where agents prefer ownership to renting and agents search for homes to purchase and for jobs. 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 house

ownership may correlate with high unemployment across regions. The model of Guler & Taskin (2011) does not include credit constraints or region-specific house prices but highlights how owners' cost of moving may interact with local labor market conditions. Head & Lloyd-Ellis (2010) build a full general equilibrium model with search for housing as well as local and non-local jobs. They allow for two types of cities and endogenize housing construction and wages and calibrate their model to high- and low-wage cities. Their model implies that homeowners are substantially less mobile than renters and have higher unemployment. This 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 and finds strong effects of innovations to 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 potentially obtaining larger lifetime income gains from moving (the "human capital" or "investment" model of migration). College graduates move substantially more than people without a college degree.

Our contribution complements the literature on potential lock-in from low or negative housing equity focussing directly on whether workers are less likely to move from locations with worse job prospects due to negative equity. 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

and potentially observed heterogeneity, such as whether a person has a college degree which may be correlated with house ownership and mobility, by including person-specific fixed effects in our regressions.[4] Aggregate data cannot isolate exogenous shocks to house prices in our view as more features of the aggregate economy impact on house prices than a parsimonious VAR can allow for. Micro data are more informative than macro data if exogenous variation in house prices is available. 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. Certain consumers may be inherently less mobile than the average consumer and inherently have low savings and low home equity. When house prices fall, such consumers will disproportionately end up with negative equity, and if they are also less mobile, a careless 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 constants can be controlled for. Our data allows us to control for such heterogeneity and our estimations are therefore less likely to capture spurious patterns. Our data is also likely to deliver precise information about long-distance moves.[5] Further, we include local labor market conditions in the estimations. For geographic mobility to help clear regional disparities in demand and supply of labor, it is not necessary that displaced individuals are geographically mobile, but rather that many workers move from depressed to booming regions.

From our data, we infer with high certainty whether households move and we 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 formulate and solve 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.

Our work is 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. These

[4]For instance, the data from the American Housing Survey follow housing units, rather than individuals, and the data from the American Community Survey is aggregated to the county level.

[5]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 mobility. However, our main focus is on mobility between states and because the number of people living in one state and receiving mail in another state is small, measurement error is likely to be limited.

authors find that the rise in household leverage during the credit boom was a strong predictor of the severity of the recession that followed: counties that experienced the largest increase in household debt before the recession ended up with the highest unemployment rates and the largest decreases in residential investment and durable consumption.

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

2 Data, regression specifications and results

2.1 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.

The first credit bureau data is from TransUnion. The 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 a 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).[7] The

[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]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

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 borrower's FICO 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 "under water" (when the amount of a mortgage balance exceeds the value of a home, i.e., when house equity is negative).

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 is 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 (2010) 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., **?**). These loans, when compared to conventional and prime mortgages, are more likely to have generated negative equity as many were originated with very low downpayments during the boom years. However, they may not be representative of the entire U.S. mortgage market due to their characteristics outlined above.[8] To check if our analysis is robust and the results are applicable to the entire country, we perform similar regressions with the 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 of "primary" individuals. Credit characteristics for everybody residing at the same address as "primary" people are also 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, similar to what is available from TransUnion, there are credit

occupied homes, loans with loan-to-value ratios exceeding 80% and no mortgage insurance (or 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, higher than 620 average FICO scores.

[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).

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

For our analysis, we construct several subsamples from the Equifax dataset. For the construction of our first and main subsample, we randomly select 50% of all individuals in Equifax who (i) have a mortgage and (ii) who owe at least 75% of their mortgage to a lender. Due to inability to construct clean equity measures with this dataset (neither direct measure of home equity or loan-to-values at origination are provided), these restrictions allow us to obtain a sample of homeowners who, potentially, can have low or negative equity in their homes if local home prices declined substantially. Hence, consumers who are close to paying their mortgage off are excluded from this subsample. We also constructed a sample of renters only which allows us to test if the relationship between mobility and equity is spurious. To further illustrate our results, we take a random 25% sample out of the entire Equifax dataset, without any restrictions on mortgage balance owed, and test our hypothesis using this sample.

In all our Equifax samples, 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. For the Equifax sample, we do not observe the amount of house equity nor details about individual mortgages—these characteristics are only available in the combined TransUnion-LP dataset. When we analyze the Equifax data, we rely on house-price appreciation in the ZIP code of the homeowner's residence (mailing address) to construct a proxy for negative home equity.

We augment borrower-loan level data from both credit bureaus with a set of macro characteristics for ZIP codes, counties, Core Based Statistical Areas (CBSAs), and states. We use the U.S. ZIP Code Database to match counties and ZIP codes.[10] County-level monthly unemployment rates and employment levels are obtained from the Bureau of Labor Statistics.[11] ZIP code level and county-level house price indices (HPI) are 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. County-level population and personal income per capita are from the Bureau of Economic Analysis.

2.2 Variable Definitions

To estimate how negative equity impacts consumers' willingness and ability to relocate for a better job, we construct the following dummy variables that capture shocks to employment possibilities in the area of their residence and the extent of equity in their homes.

[10] http://www.zip-codes.com/zip-code-database.asp.

[11] 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.

Let Δu_{rt} denote the change in the annual unemployment rate in region r at time t (where region is either county or state), 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 $\text{Shock}^u_{rt} = \Delta u_{rt} - \Delta u_t$. Similarly, a shock to log-employment is defined as $\text{Shock}^e_{rt} = \Delta e_{rt} - \Delta e_t$, where Δe_{rt} is the change in annual log-employment in region r at time t, and Δe_{rt} is its average across all regions.

Based on the sign of Shock^u_{rt} and Shock^e_{rt}, we create two dummy variables indicating if the regional shock is positive or negative (i.e., relatively strong local labor market conditions or relatively weak local labor market conditions). When Shock^u_{rt} (Shock^e_{rt}) is positive (negative), the dummy variable "Neg. shock (cty/st)" takes the value of one. The dummy variable "Pos. shock (cty/st)" equals one if Shock^u_{rt} (Shock^e_{rt}) takes a negative (positive) value. That is, the regional shock is positive if regional employment growth (the change in the unemployment rate) is higher (lower) than the national employment growth (the change in the national unemployment rate).

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 either locally or out of state. Similar to Elul, Souleles, Chomsisengphet, Glennon & Hunt (2010) and Demyanyk, Van Hemert & Koijen (2011), we define housing equity for property i at time t as:

$$\%\text{Equity}_{i,t} = 100\% - \frac{\text{Loan}_{i,0}}{\text{Value}_{i,0}} \times \frac{\text{Zip HPI}_{i,0}}{\text{Zip HPI}_{i,t}}, \tag{1}$$

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 ($\text{Zip HPI}_{i,t}$). When the value of a home exceeds the amount of the mortgage, then home equity is positive. When a home is worth less than the mortgage amount, home equity is negative, a phenomenon is known as a mortgage being "under water."

We create three dummy variables that group homeowners into three categories based on the estimated amount of equity they have in their homes. A dummy variable "Equity $< 0\%$" equals one if home equity is negative. Similarly, dummy variables "Equity$[0, 25\%]$" and "Equity $> 25\%$" equal one if home equity is positive but low (between 0 and 25%), or above 25% of the home value, respectively. We then interact each of the dummy variables for regional shocks with the equity dummies. As a result, we obtain six dummy variables. In our empirical analysis, out of the six categories, we omit the group of homeowners with positive but small equity residing in regions with favorable unemployment (employment) shocks. Table 1 summarizes these dummy variables along with the other variables we use in our empirical analysis.

For the analysis based on Equifax data, we cannot measure home equity as we do not know mortgage details at origination or thereafter in this dataset. To proxy for this measure, we use

biennial growth in house prices ("HP growth") in the ZIP code where an individual lives. Similarly to the TransUnion equity measures, we construct a dummy variable "HP growth $< 0\%$" ("HP growth $> 0\%$") that equals one if biennial house-price growth is negative (positive). We also interact these variables with the dummies "Pos. shock (cty/st)" and "Neg. shock (cty/st)" to explore if negative equity, that is likely to be the result of declining house prices in the area of residence, hampers mobility out of areas that experience negative employment shocks.

2.3 Moving Rates

Table 3 shows that moving rates declined substantially from 2006 to 2009. As shown in the top panel of Table 3, the overall moving rate, computed as a change in ZIP code, declined from approximately 10% to 8% for Equifax households, and from 9% to 5.6% for TrasUnion households. The moving rate across counties within the same state declined from 2.6% to 2.2% in Equifax and from 2.4% to 1.4% in TransUnion. The moving rate from one state to another declined from 2.4% to 2.0% in Equifax and from 2.7% to 1.3% in TransUnion. TransUnion households are all homeowners, while Equifax households include both homeowners and renters, which might explain why moving rates are a bit lower in TransUnion to begin with.

2.4 Regression Specification and Results

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

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

where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and 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. Other controls include a foreclosure indicator, credit scores, income and population in the area of residence, and age (in Equifax) or age structure of the population in the area of residence (in TransUnion). δ_j denotes region (county or state) fixed effects and μ_t and ν_i are time and individual fixed effects, respectively. Explanatory variables are lagged one year for the analysis to reflect credit or labor market conditions before the decision to move is taken. We cluster standard errors by individuals in the regressions. We estimate the probability of moving to another county within the state ("local moves") or moving to another state ("non-local moves") which is the relevant move for geographical relocation of workers to jobs (one may commute between ZIP codes or neighboring counties). Comparing county versus state moves will be informative about the relative costs of moving shorter versus longer distances.

2.4.1 Results: TransUnion

Table 4 displays our main results. As previously discussed, all regressions include time and county/state fixed effects and, importantly, individual fixed effects which control for all non time-varying individual traits. The top six regressors in the table are our main results regarding predicted home equity and geographical labor market clearing, with the top two regressors being interactions of local labor market conditions with dummies for negative equity, the third regressor showing the effect of low but positive equity with a positive change in the regional unemployment rate (weak local labor market) labeled as "negative shock" (the left-out dummy is positive regional shocks and low individual equity), and the bottom two regressors comprise interactions of dummies for individuals with equity above 25 percent of house value and local labor market conditions.

It is instantly obvious from the results that low equity hampers mobility consistent with Ferreira et al. (2010) and Ferreira et al. (2011): for local moves, mobility is lowest in the groups with negative equity and highest in the groups with highest equity. Most likely, a large fraction of individuals with high equity moves to upgrade housing and while people with low equity might want to downgrade housing in the absence of fixed costs, they are more reluctant to do so in the face of such costs. Young people, in particular, who expect increasing income and expect to upgrade housing over the life-cycle, would be reluctant to downgrade housing in the face of an economic setback. Local mobility across all three equity groups is lower when the county is hit by a negative shock—our interpretation is that negative regional shocks are correlated with individual income shocks so fewer people move to improve housing in bad times.

The local mobility patterns do not, however, systematically carry over to cross-state moves as found by Donovan & Schnure (2011) using aggregate data. Interestingly, individuals with negative equity are as likely to move out of state when the state economy is hit by negative shocks as are individuals with high housing equity. This pattern is robust to whether credit score, mortgage age, and population size are controlled for. The size of the estimated coefficient to the "Negative shock $\times$ negative equity" is 0.28 (when not controlling for credit score, etc.) which implies that individuals with negative equity are 0.28 percent more likely to move out of state in bad years than individuals in the left-out group with low but positive equity. The coefficient is of similar magnitude as that for individuals with high equity in downturns. It appears that individuals with negative equity are perfectly willing to take their housing losses and move on if opportunities arise in other states. Individuals with low positive equity are less likely to leave the state of residence, whether the economy is hit by positive or negative shocks, probably because they hope to maintain their housing (and other) consumption rather than pay the cost of moving. For this group one might talk about a lock-in but the effect is not likely to have any noticeable impact on the average U.S. level of unemployment. 20 percent of our sample is in the category of having very low equity and facing a negative economic shock, and our TransUnion sample is itself capturing the fraction

of population with low equity to begin with so lock-in is not likely to be common for the full population. The coefficients can also be compared to the average mobility from state to state in the TransUnion sample which was about 3 percent in 2006–2007, falling to 1.3 percent in 2009. Our interpretation, based on the findings discussed, is that the large drop in interstate mobility over this period is a reflection of a drop in the number of job offers that workers receive, and only marginally affected by home equity issues.

Foreclosure significantly predicts interstate, but not local moves. Obviously, foreclosure implies that there is no further sales costs and former homeowners can therefore accept job offers in other states at less cost. This further strengthens the finding that collapsing housing equity is not a significant cause of unemployment. Income growth in the county/state of residence hampers mobility, as expected, again implying that people move to opportunities.[12] Young and older people move less locally but move more across states for job opportunities and retirement, respectively, as captured by the coefficients to the share of less than 30 year olds or 55 years of age or older in the regression.

We include further regressors in the second and fourth columns. A high credit score correlates with higher propensity to move within and across states. Individuals with a relatively good score compared to their average score (absorbed in the fixed effect) are likely to find a better interest rate than their current rate which lowers the "cost" of moving. Mortgage age significantly predicts interstate moving. In the TransUnion sample, most mortgages are recently originated and most mortgages are subprime, with penalties for early prepayment (typically within the first two years). It is therefore optimal to wait until the expiration of the prepayment penalty period before moving. Finally, we include population in the county/state and find a negative coefficient. This captures that in large counties one may more easily move to upgrade housing or neighborhood quality without leaving the county while in a large state, such as California, it is possible to move to another labor market in another part of the state or even to retire in a different climate zone and still remain within the state.

Table 5 examines if the results are robust. The first two columns are estimated on the sample of "non-recourse states" where homeowners can default on their mortgage without lenders being able to pursue other avenues for recovering the mortgage debt besides taking over the property. The sample is less than half of the sample in Table 4 but the results are very similar even if a few coefficients have turned insignificant, such as the coefficient to the negative shock to the state economy times high equity and the coefficient to the score for interstate moves. The coefficient on the fraction of young people becomes very imprecisely estimated for out of state moves because

[12]Technically, our regression includes the level of income, but because county/state dummies are included the variation driving the results is purely intertemporal: the results should be interpreted as capturing income growth rather than levels—this interpretation is also strengthened because the short duration of our sample implies that deviations from the person-specific means (captured by the fixed effect) are recent.

the low number of non-recourse states limits the variation in the regressor. Overall, the results of these columns do not cast doubt on the conclusions from the full sample.

The third and fourth columns define shocks from drops in employment rather than from unemployment changes in the previous table. The results are very similar to those of the previous table. One difference is that the coefficient to the negative shock interacted with low positive equity is positively significant in this table, which further suggests there is no lock-in. The coefficient is much smaller than that for the negative equity times negative shocks confirming no lock-in in depressed regions.

The last column considers vacancies as an indicator of state-level economic shocks. For vacancies, we find that people leave states with lower than national average vacancies almost independently of the amount of house equity, although the coefficient is still the largest for the group with negative equity. On the whole, the results of using vacancies are very similar to those found using unemployment.

Table 6 considers MSAs rather than states as the local labor markets and examines if the results using MSAs are similar to the results found for states. We find that this is mainly the case. Negative equity and negative employment shocks predict outward mobility as does high equity and negative employment shocks. Fewer coefficients are significant than for states, maybe because fewer MSAs correspond to separate labor markets, but the results generally are similar to those obtained using states.

2.4.2 Results: Equifax

Table 7 performs similar regressions for the Equifax sample for which we do not have equity measures. Instead, we interact labor market conditions with house price growth over the previous two years. We only separate between positive and negative house price growth as we cannot identify if homeowners have negative or positive house equity. The two left-most columns consider individuals with relatively high mortgage balances in order to isolate homeowners who are most likely to have negative equity after house price declines. The picture that emerges from Table 7 is similar to that from the TransUnion regressions. In particular, homeowners are more likely to leave a state with negative labor market shocks and this pattern is not dependent on house prices. Falling house prices are associated with lower mobility within states and, somewhat puzzlingly, when house prices display positive growth individuals are the least likely to move out of the county if labor market shocks are negative (probably because homeowners can borrow against equity in their homes). Other regression coefficients are also broadly similar to those of the TransUnion tables. In the two rightmost columns, we consider the full Equifax sample. The main difference in the results, compared to the first two columns, is that negative house price growth is systematically associated with lower mobility at the county as well as the state level. This results is not driven by

homeowners with low equity (the sample in the first two columns) and our interpretation is that for this sample, the correlation of house prices with local conditions dominates any effects of low house prices approximating low house equity.

Table 8 considers renters. For renters, we find no impact of house prices on interstate mobility while for mobility across counties the coefficient to the negative shock times positive house price growth is negative. This is puzzling; however, the results for renters are not central to our story but serve to ascertain that the patterns found for owners are not picking up variables correlated with house equity, rather than the impact of equity itself.

3 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 and its wealth (if positive) is passed on as an accidental bequest. Houses are liquidated at death so newborns receive only liquid assets.

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

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). We allow for the selling cost to be higher for non-local moves ($\chi + \omega$, $\omega > 0$) to capture a preference for the current location. Houses depreciate at the rate δ_h and homeowners can choose the degree of maintenance.[13] 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 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 are subject to household-specific risk in labor earnings and house-price risk common to residents of the same region. Working-age households can be employed or unemployed.

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 $\log \nu_t \sim N(-\sigma_\nu^2/2, \sigma_\nu^2)$, while $\phi_t = 1$ for employed workers but $\phi_t = \lambda < 1$ for unemployed

[13] 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.

individuals—i.e., unemployment reduces current income by a certain proportion. In turn, permanent income is $P_t = P_{t-1}\gamma_t\epsilon_t\varsigma_t$. Thus, permanent income growth, $\Delta \log P_t$, is the sum of a non-stochastic life-cycle component, $\log \gamma_t$, an idiosyncratic permanent shock, $\log \epsilon_t \sim N(-\sigma_\epsilon^2/2, \sigma_\epsilon^2)$, 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 geographical regions explicitly but we do 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 it is not accepted. Since we do not model geographical locations explicitly, we assume that homeowners believe the region they would be moving to is identical to their current region in terms of the probabilities described above.

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, $W_t = bP_R$, $\forall t > R$.[14]

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.[15] In order to keep the model tractable, there are no built-in house price 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.[16] 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

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

[15]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.

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

government expenditures that do not affect households at the margin.

3.1 Calibration

The calibration is constructed to reproduce three statistics from the Survey of Consumer Finances: 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

For computational reasons, one period is one 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 $\sigma = 2$.

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).[17] 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.

[17] 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.

In our benchmark case, households who are employed remain employed 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 offer with a 5% 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 Retirement Survey and the Social Security Administration. Cocco et al. (2005), using PSID data, report that the ratio of average income for retirees to average income in the last working year before retirement is 68 percent. Our choice is in between these two numbers.

Market arrangements

The minimum down payment is 5 percent, below the 25 percent average down payment for the period 1963–2001 reported by the Federal Housing Finance Board but in line with pre-crisis terms. The buying cost is 2 percent while the selling cost is 6 percent (a typical realtor fee). There is an additional 3 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 moving rate in our baseline calibration is roughly 10 percent a year in line with the rates calculated from the different datasets used in our previous section.

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.[18] 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.

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

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 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.[19] 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, $\tau_m = 1$.

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 $\sigma_\varrho^2 = 0.0132$—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 6.5 percent annually.

Patterns of homeownership and wealth

Figure 1 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

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

(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 1 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 afterward. 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 2. We focus on moving rates for owners because renters in the model may "move" every period as they can adjust housing services without cost. The average moving rate for homeowners is roughly 13 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. Also, labor income uncertainty decreases with age.

Panel *(b)* of Figure 2 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, 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 2 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 2 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) were 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 data very 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.

3.2 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 a number of 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 four 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 five periods of the simulations in the tables that follow but results are similar if more periods are included (we have five years of actual data from TransUnion and Equifax).

Because of our modeling choices, moving rates for renters are not meaningful because they 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 slightly lower

when houses depreciate regardless of employment status (15.7 percent in periods of house-price appreciation versus 14.2 percent in periods of stable or falling house prices). Also, the moving rate for unemployed owners is more than twice as high as the rate of employed owners regardless of house-price appreciation. Since non-local moves are meant to be comparable to out-of-state moves when using credit bureau data, moving rates are also significantly higher for unemployed homeowners who are much more responsive to non-local job offers (25.9 percent versus 0.7 percent). Moving rates do not differ 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 24.4 percent in periods of rising house prices).

The previous cross-tabulations are not consistent with a lock-in effect: unemployed homeowners are more likely to accept non-local job offers, should they receive any, than employed homeowners and housing depreciation does therefore not hinder relocation. This finding could be the result of simulated households not allowing themselves to end up with negative equity. 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. Since 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 (5 percent of households in the baseline simulation hold negative equity, 15 percent have low equity and the rest have equity above 25 percent; mean equity is 60 percent). Nonetheless, the simulated sample is in line with the Equifax data and can still inform our empirical analysis. For these regressions, we interact employment status (employed or unemployed in the previous year) with dummies that classify households in the same three equity groups we use in our empirical specification (negative equity, 0–25 percent equity and over 25 percent). The excluded category in the regressions is employed owners in the low but positive equity group. The interpretation of the coefficients for the remaining interactions is moving more or less than this group. We include age, income and having foreclosed within the last two years as additional controls.

Results from linear regressions, columns (1)–(2) of Table 11, indicate that unemployed households with negative equity in periods of housing depreciation are less likely to move locally (about 7 percent less than the excluded group) but more likely to move out of the region (about 22 percent more likely than the excluded group). Unemployed households with negative equity are slightly less likely to move out of the region than other unemployed households, but the effect of home equity for this group is non-monotonic as households with more equity can simply use it to prop-up nondurable consumption during an unemployment spell but also have more resources to move out of the region if receiving a job offer and so desire. Age affects local moves but has no effect on non-local moves because the arrival of job offers is not correlated with age in the model. House-

holds with higher income are more likely to move out of the region (which is more expensive than moving locally) and foreclosure clearly affects local moves as we force households to sell their house and stay in the same region during the period they foreclose. Results in columns (3)–(4) which include both household fixed effects and time fixed effects are very similar, which is not surprising since our households are ex-ante identical. Table 12 summarizes further regressions in which we simply interact employment status with dummies for housing appreciation and depreciation with similar conclusions. Unemployed homeowners are less likely to move locally in periods of housing depreciation.

Although these 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. We do not keep track of actual locations in our stylized model 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.[20] In local strong regions, 80 percent of the job offers received by unemployed households are local versus 60 percent in the local weak regions. All other parameters are the same as in the baseline calibration. We simulate 27 regions of each type, 54 total, with one third experiencing housing appreciation, one third experiencing housing depreciation and one third with stable house prices just as in the former experiment. We perform regressions in which we include interactions of region type (local strong or local weak) and dummies that classify households in the three home equity groups previously described, the excluded category being households with 0–25 percent equity in strong local regions. We include additional controls analogous to those in the TransUnion regressions: the fraction of the population younger than 30 or older than 55, income per capita in the area, and a dummy variable identifying households who had foreclosed in the previous 24 months.

Table 13, columns (1) and (2), summarizes the results. Consistent with our findings using TransUnion data, households with negative equity in local weak regions are less likely to move locally but more likely to move out of the region when compared to the excluded category. Households with negative equity in strong regions are also more likely to move out of region than the excluded group, but less like to move than households in weak regions. Also, households with high equity are more likely to move locally and out of region than the excluded group. The important point is that these results are qualitatively the same as those in Table 12 using actual employment status information, which indicates that our empirical findings using credit bureau data can safely

[20]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.

be interpreted as households moving out of 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 same rate.

The coefficients estimated using simulated data are in general higher (in absolute value) than those estimated using TransUnion or Equifax data. Note the model assumes no correlation between income and house prices and, moreover, homeowners can sell their home whenever they desire to move. In reality, mobility out of areas with weak labor markets might be reduced somewhat not necessarily because home prices go down but because homes cannot be sold quickly or at all, or because income is low.

4 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 county or state. We relate the likelihood of moving to economic conditions in their area of residence and to the amount of equity in their homes. We conclude that in good times, with positive labor market shocks, negative equity tend to "lock" people in their homes as it is costly to sell the house, walk away from the mortgage, or pay for two houses. However, in bad times, when unemployment is high and job opportunities are limited, negative house equity is not "locking" individuals in their homes and, therefore, not limiting geographical labor market mobility. We formulate and simulate a model of forward looking optimizing consumers who consume non-durables and housing services, face credit constraints and fixed costs of buying and selling houses. The model demonstrates that our empirical findings can be rationalized by the model under reasonable calibration.

References

Barnichon, R., Elsby, M., Hobijn, B. & Sahin, A. (2011), Which industries are shifting the beveridge curve? *Federal Reserve Board, Working Paper*.

Barnichon, R. & Figura, A. (2011), What drives matching efficiency? A tale of composition and dispersion. *Finance and Economics Discussion Series 2011-10*, Federal Reserve Board.

Bayer, C. & Juessen, F. (2011), On the dynamics of interstate migration: Migration costs and self-selection. Working Paper.

Campbell, J. & Cocco, J. F. (2003), 'Household risk management and optimal mortgage choice', *Quarterly Journal of Economics* **118**(4), 1149–1194.

Chan, S. (2001), 'Spatial lock-in: Do falling house prices constrain residential mobility?', *Journal of Urban Economics* **49**(3), 567–86.

Cocco, J. F. (2005), 'Portfolio choice in the presence of housing', *Review of Financial Studies* **18**(2), 535–567.

Cocco, J. F., Gomes, F. J. & Maenhout, P. J. (2005), 'Consumption and portfolio choice over the life cycle', *Review of Financial Studies* **18**(2), 491–533.

Coulson, N. E. & Fisher, L. M. (2009), 'Housing tenure and labor market impacts: The search goes on', *Journal of Urban Economics* (May), 252–264.

Coulson, N. & Fischer, L. (2002), 'Tenure choice and labour market outcomes', *Housing Studies* **17**(1), 35–49.

Demyanyk, Y. & Van Hemert, O. (2010), 'Understanding the subprime mortgage crisis', *Forthcoming Review of Financial Studies* .

Demyanyk, Y., Van Hemert, O. & Koijen, R. (2011), Determinants and consequences of mortgage default. Working Paper Federal Reserve Bank of Cleveland.

Díaz, A. & Luengo-Prado, M. J. (2008), 'On the user cost and homeownership', *Review of Economic Dynamics* **11**(3), 584–613.

Díaz, A. & Luengo-Prado, M. J. (2010), 'The wealth distribution with durable goods', *International Economic Review* **51**, 143–170.

Donovan, C. & Schnure, C. (2011), Locked in the house: Do underwater mortgages reduce labor market mobility? Working Paper Freddie Mac.

Elul, R., Souleles, N. S., Chomsisengphet, S., Glennon, D. & Hunt, R. (2010), 'What "triggers" mortgage default?', *American Economic Review (P&P)* **100**, 490–500.

Engelhardt, G. V. (2003), 'Nominal loss aversion, housing equity constraints, and household mobility: Evidence from the united states', *Journal of Urban Economics* **53**(1), 171–95.

Feenberg, D. & Coutts, E. (1993), 'An introduction to the TAXSIM model', *Journal of Policy Analysis and Management* **12**(1), 189–194.

Ferreira, F., Gyourko, J. & Tracy, J. (2010), 'Housing busts and household mobility', *Journal of Urban Economics* **68**(1), 34–45.

Ferreira, F., Gyourko, J. & Tracy, J. (2011), 'Housing busts and household mobility: An update', *NBER Working Paper* (17405).

Gallin, J. H. (2004), 'Net migration and state labor market dynamics', *Journal of Labor Economics* **22**, 1–21.

Green, R. K. & Hendershott, P. H. (2001), 'Home ownership and unemployment in the U.S.', *Urban Studies* **38**(9), 1509–20.

Guler, B. & Taskin, A. A. (2011), Homeownership and unemployment: The effect of market size. Working Paper.

Halket, J. (2011), Do households use home ownership to insure themselves? evidence across us cities. mimeo.

Harding, J. P., Rosenthal, S. S. & Sirmans, C. (2007), 'Depreciation of housing capital, maintenance, and house price inflation: Estimates from a repeat sales model', *Journal of Urban Economics* **61**(2), 193–217.

Head, A. & Lloyd-Ellis, H. (2010), Housing liquidity, mobility, and the labour market. Queens Economics Department Working Paper.

Hryshko, D., Luengo-Prado, M. J. & Sorensen, B. E. (2011), 'House prices and risk sharing', *Journal of Monetary Economics* **57**(8), 975–987.

Kennan, J. & Walker, J. R. (2011), 'The effect of expected income on individual migration decisions', *Econometrica* **79**.

Lee, D. & van der Klaauw, W. (2010), An introduction to the frbny consumer credit panel. Federal Reserve Bank of New York Staff Reports, no. 479.

Li, W. & Yao, R. (2007), 'The life-cycle effects of house price changes', *Journal of Money, Credit and Banking* **39**(6), 1375–1409.

Mian, A. & Sufi, A. (2009), 'The consequences of mortgage credit expansion: Evidence from the u.s. mortgage default crisis', *Quarterly Journal of Economics* **124**(4), 1449–1496.

Mian, A. & Sufi, A. (2010), 'The great recession: Lessons from microeconomic data', *American Economic Review* **100**(2), 51–56.

Molloy, R., Smith, C. L. & Wozniak, A. (2010), Internal migration in the us: Updated facts and recent trends. Working Paper, Federal Reserve Board.

Munch, J. R., Rosholm, M. & Svarer, M. (2006), 'Are homeowners really more unemployed?', *Economic Journal* **116**(514), 991–1013.

Munch, J. R., Rosholm, M. & Svarer, M. (2008), 'Home ownership, job duration, and wages', *Journal of Urban Economics* **63**(1), 130–145.

Munnell, A. H. & Soto, M. (2005), What replacement rates do households actually experience in retirement? CRR Working Paper No. 2005-10.

Oswald, A. (1997), 'Thoughts on nairu', *Journal of Economic Perspectives* **11**, 227–228.

Prescott, E. C. (2004), 'Why do Americans work so much more than Europeans?', *Federal Reserve Bank of Minneapolis Quarterly Review* (July), 2–13.

Schmitt, J. & Warner, K. (2011), Deconstructing structural unemployment. Center for Economic and Policy Research.

Schulhofer-Wohl, S. (2011), Negative equity does not reduce homeowners' mobility, NBER Working Papers 16701, National Bureau of Economic Research, Inc.

Sinai, T. & Souleles, N. S. (2005), 'Owner-occupied housing as a hedge against rent risk', *Quarterly Journal of Economics* **120**(2), 763–789.

Sterk, V. (2010), Home equity, mobility, and macroeconomic fluctuations. Working Paper. De Nederlansche Bank and University of Amsterdam.

Storesletten, K., Telmer, C. & Yaron, A. (2004), 'Consumption and risk sharing over the life cycle', *Journal of Monetary Economics* **51**(3), 609–633.

Table 1: Descriptive Statistics: TransUnion

Variable	Mean	Std. Dev.	Mean	Std. Dev.
	County level		**State level**	
Moving rate	0.02	0.14	0.02	0.15
Shocks to regional unemployment rate				
Neg. shock × equity < 0%	0.09	0.29	0.10	0.29
Pos. shock × equity < 0%	0.03	0.16	0.02	0.15
Neg. shock × equity [0,25]%	0.21	0.41	0.20	0.40
Pos. shock × equity [0,25]%	0.18	0.39	0.19	0.40
Neg. shock × equity > 25%	0.23	0.42	0.21	0.40
Pos. shock × equity > 25%	0.26	0.44	0.28	0.45
Neg. shock	0.53	0.50	0.50	0.50
Shocks to regional employment				
Neg. shock × equity < 0%	0.06	0.24	0.08	0.28
Pos. shock × equity < 0%	0.06	0.21	0.04	0.18
Neg. shock × equity [0,25]%	0.25	0.43	0.23	0.42
Pos. shock × equity [0,25]%	0.15	0.36	0.17	0.37
Neg. shock × equity > 25%	0.30	0.46	0.30	0.46
Pos. shock × equity > 25%	0.19	0.31	0.18	0.39
Neg. shock	0.60	0.49	0.62	0.49
Vacancy Rate	–	–	3.00	0.71
Per capita income (× 1,000)	20.59	5.35	19.39	2.20
Fraction of population, age below 30	0.18	0.03	0.18	0.01
Fraction of population, age above 55	0.31	0.05	0.32	0.03
Population (× 1,000)	1,760	2,406	18,703	13,303
	Entire Sample			
Foreclosure dummy	0.03	0.17		
Credit Score	780.3	134.7		
Mortgage age (months)	24.1	19.7		
Equity < 0%	0.12	0.32		
Equity [0,25]%	0.40	0.49		
Equity > 25%	0.49	0.50		

Note: "Moving rate" is a dummy variable that equals one if an individual changed his or her mailing address within last year. "Neg. (Pos.) shock" to unemployment is a dummy variable that equals one if the annual change in regional unemployment rate relative to the national average change is positive (negative); equals zero otherwise. "Neg. (Pos.) shock" to employment is a dummy variable that equals one if the annual change in regional log employment relative to the national average change is negative (positive); equals zero otherwise. "Foreclosure dummy" equals one if a borrower at time t is in foreclosure (source: CoreLogic). "Credit Score" is a VantageScore provided by TransUnion. "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). All listed variables except moving rates have been lagged one year for the analysis.

TABLE 2: DESCRIPTIVE STATISTICS: EQUIFAX

Variable	Mean	Std. Dev.	Mean	Std. Dev.
	County level		**State level**	
Moving rate	0.016	0.127	0.018	0.131
Shocks to regional unemployment rate				
Neg. shock × HP growth < 0%	0.05	0.21	0.05	0.21
Pos. shock × HP growth < 0%	0.03	0.17	0.03	0.16
Neg. shock × HP growth > 0%	0.50	0.50	0.49	0.50
Pos. shock × HP growth > 0%	0.43	0.50	0.44	0.50
Neg. shock	0.54	0.50	0.53	0.50
Per capita income (× 1,000)	41.1	10.2	38.4	5.40
Population (× 1,000)	1,318	1,940	14,344	11,073
	Entire Sample			
Foreclosure dummy	0.02	0.13		
Credit Score	721.6	96.0		
Consumer Age	44.7	9.1		
Biennial HP growth < 0%	0.07	0.26		
Oldest mortgage age (months)	106.3	63.5		

Note: "Moving rate" is a dummy variable that equals one if an individual changed his or her mailing address within the last year. "HP growth" is a variable that measures biennial growth rates of house prices in the ZIP code of a consumer's residence at time t. The house price data is from CoreLogic. "Mortgage age" is age, in months, of an oldest mortgage account an individual ever had. "Credit Score" is a credit score provided by Equifax. "Foreclosure dummy" equals one if an individual had at least one foreclosure in the past 24 months. "Neg. (Pos.) shock" to unemployment is a dummy variable that equals one if the annual change in regional unemployment rate relative to the national average change is positive (negative); equals zero otherwise. All listed variables except moving rates have been lagged one year for the analysis.

Table 3: Moving Rates in credit bureau data

Year	ZIP	County	State
	Equifax, FRBNY CCP		
2006	0.101	0.026	0.024
2007	0.102	0.026	0.024
2008	0.092	0.024	0.023
2009	0.084	0.022	0.020
Overall	0.095	0.025	0.023
	TransUnion		
2006	0.091	0.024	0.027
2007	0.093	0.024	0.028
2008	0.079	0.021	0.020
2009	0.056	0.014	0.013
Overall	0.080	0.022	0.022

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 previous year. The second column shows the fraction of people who moved within the same state changing counties. The third column shows moving rates to different states.

TABLE 4: TRANSUNION. PROBABILITY OF MOVING TO ANOTHER LOCATION.

	County		**State**	
Neg. shock (cty/st) × equity < 0%	–0.65***	–0.63***	0.28***	0.38***
	(–6.59)	(–6.44)	(3.50)	(4.73)
Pos. shock (cty/st) × equity < 0%	–0.41***	–0.41***	–0.41***	–0.32**
	(–2.92)	(–2.89)	(–2.83)	(–2.23)
Neg. shock (cty/st) × equity [0, 25]%	–0.14**	–0.13**	0.06	0.06
	(–2.32)	(–2.29)	(1.12)	(1.18)
Pos. shock (cty/st) × equity [0, 25]%	excluded	excluded	excluded	excluded
	group	group	group	group
Neg. shock (cty/st) × equity > 25%	0.30***	0.32***	0.35***	0.11
	(3.96)	(4.23)	(4.70)	(1.49)
Pos. shock (cty/st) × equity > 25%	0.58***	0.61***	0.58***	0.36***
	(7.50)	(7.85)	(7.89)	(4.75)
Foreclosure dummy	0.21	0.21	0.32***	0.37***
	(1.41)	(1.45)	(2.66)	(3.05)
Log per capita inc. (cty/st)	–1.18***	–1.13***	–3.95**	–4.11***
	(–8.09)	(–6.94)	(–2.56)	(–2.71)
Ages below 30, fraction (cty/st)	–6.77***	–5.27***	81.64***	59.91***
	(–4.04)	(–3.10)	(5.73)	(3.26)
Ages above 55, fraction (cty/st)	–3.40***	–3.63***	7.32	–13.12
	(–3.93)	(–4.11)	(0.53)	(–0.81)
Log score		0.70**		0.62**
		(2.57)		(2.50)
Mortgage age		–0.09		3.83***
		(–0.37)		(11.99)
Log population (cty/st)		–0.12***		–5.93*
		(–4.65)		(–1.94)
Time effects	Y	Y	Y	Y
County effects	Y	Y	N	N
State effects	N	N	Y	Y
Individual effects	Y	Y	Y	Y
N	870857	870857	887376	887376

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 county or state 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 5: TransUnion. Probability of moving to another location.

	Non-recourse states		Empl. growth		Vacancy rate
	County	**State**	**County**	**State**	**State**
Neg. shock (cty/st) × equity < 0%	–0.68***	0.36***	–0.42***	0.58***	0.40***
	(–4.40)	(2.92)	(–3.81)	(6.30)	(4.65)
Pos. shock (cty/st) × equity < 0%	0.27	0.14	–0.50***	–0.26*	0.18
	(0.91)	(0.61)	(–4.76)	(–1.90)	(1.61)
Neg. shock (cty/st) × equity [0, 25]%	–0.07	0.02	0.03	0.15**	0.20***
	(–0.58)	(0.22)	(0.42)	(2.22)	(2.66)
Pos. shock (cty/st) × equity [0, 25]%	excluded group	excluded group	excluded group	excluded group	excluded group
Neg. shock (cty/st) × equity > 25%	0.37***	–0.18	0.65***	0.23***	0.31***
	(2.76)	(–1.49)	(8.49)	(2.68)	(3.49)
Pos. shock (cty/st) × equity > 25%	0.51***	0.42***	0.52***	0.40***	0.27***
	(3.74)	(4.25)	(7.50)	(4.37)	(3.57)
Foreclosure dummy	0.19	0.08	0.21	0.37***	0.38***
	(0.83)	(0.59)	(1.41)	(3.10)	(3.15)
Log per capita inc. (cty/st)	–2.43***	1.45	–1.20***	–3.88**	–5.17***
	(–8.29)	(0.32)	(–7.33)	(–2.56)	(–3.45)
Ages below 30, fraction (cty/st)	–25.71***	102.35	–5.37***	62.21***	53.91***
	(–7.03)	(1.64)	(–3.16)	(3.40)	(2.90)
Ages above 55, fraction (cty/st)	–14.23***	7.13	–3.74***	–11.10	–1.46
	(–7.23)	(0.14)	(–4.23)	(–0.68)	(–0.09)
Log score	1.36***	–0.25	0.73***	0.58**	0.56**
	(3.03)	(–0.84)	(2.66)	(2.37)	(2.29)
Mortgage age	2.21***	2.41***	–0.20	3.82***	3.76***
	(5.42)	(5.88)	(–0.83)	(11.96)	(11.79)
Log population (cty/st)	–0.40***	0.80	–0.11***	–1.43	–3.61
	(–9.24)	(0.10)	(–4.17)	(–0.46)	(–1.17)
Time effects	Y	Y	Y	Y	Y
County effects	Y	N	Y	N	N
State effects	N	Y	N	Y	Y
Individual effects	Y	Y	Y	Y	Y
N	388540	388672	870857	887376	885192

Note: 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 county or state 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 6: TRANSUNION. PROBABILITY OF MOVING TO ANOTHER MSA.

	Empl. growth	Unempl. rate	Vacancy rate
Neg. shock (MSA) × equity $< 0\%$	0.24*	0.11	0.34***
	(1.94)	(0.98)	(2.75)
Pos. shock (MSA) × equity $< 0\%$	–0.24**	–0.30*	–0.17
	(–1.99)	(–1.91)	(–1.42)
Neg. shock (MSA) × equity $[0, 25]\%$	0.00	0.02	0.07
	(0.02)	(0.36)	(0.81)
Pos. shock (MSA) × equity $[0, 25]\%$	excluded	excluded	excluded
	group	group	group
Neg. shock (MSA) × equity $> 25\%$	0.42***	0.30***	–0.08
	(4.13)	(3.22)	(–1.02)
Pos. shock (MSA) × equity $> 25\%$	0.35***	0.47***	0.26***
	(3.73)	(4.94)	(3.37)
Foreclosure dummy	0.49***	0.49***	0.54***
	(3.04)	(3.01)	(3.22)
Log per capita inc. (MSA)	–3.18**	–3.66**	–2.62
	(–2.15)	(–2.43)	(–1.63)
Ages below 30, fraction (cty)	66.02***	66.29***	68.87***
	(5.53)	(5.54)	(5.09)
Ages above 55, fraction (cty)	15.38*	15.35*	20.03*
	(1.65)	(1.65)	(1.95)
Log score	1.49***	1.52***	0.39
	(4.37)	(4.45)	(1.13)
Mortgage age	6.01***	5.99***	5.30***
	(14.69)	(14.66)	(12.08)
Log population (MSA)	1.29	0.30	3.05
	(0.64)	(0.15)	(1.42)
Time effects	Y	Y	Y
MSA effects	Y	Y	Y
Individual effects	Y	Y	Y
N	830303	830303	659176

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 county or state 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 7: EQUIFAX. PROBABILITY OF MOVING TO ANOTHER LOCATION.

	Mortgage balance			
	High		**All**	
	County	State	County	State
Neg. shock (cty/st) × HP growth < 0%	–0.09***	0.05*	–0.22***	–0.22***
	(–3.27)	(1.88)	(–5.05)	(–4.39)
Pos. shock (cty/st) × HP growth < 0%	–0.11***	0.03	–0.21***	–0.18***
	(–3.21)	(0.83)	(–4.22)	(–3.18)
Neg. shock (cty/st) × HP growth > 0%	–0.21***	0.04*	–0.19***	0.01
	(–10.13)	(1.87)	(–5.69)	(0.17)
Pos. shock (cty/st) × HP growth > 0%	excluded group	excluded group	excluded group	excluded group
Foreclosure dummy	0.18	0.52***	2.36***	1.10***
	(1.06)	(3.92)	(16.42)	(9.33)
Log per capita inc. (cty/st)	0.73***	0.13	0.25**	–0.48
	(8.58)	(0.22)	(2.26)	(–0.48)
Log population (cty/st)	0.03**	–4.30***	–0.01	2.83**
	(2.05)	(–5.50)	(–0.73)	(2.20)
Age	–0.34***	–0.07	–0.35***	–0.17***
	(–8.43)	(–1.62)	(–23.00)	(–11.85)
Age sq./100	0.28***	0.03	0.35***	0.15***
	(6.45)	(0.65)	(20.58)	(9.27)
Log score	0.58***	0.38***	–0.78***	0.60***
	(3.99)	(3.09)	(–8.07)	(6.29)
Mortgage age	0.06	0.01	–0.15***	–0.24***
	(1.43)	(0.32)	(–6.50)	(–10.18)
N	2937937	2940864	1204748	1206084

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 county or state 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 8: Equifax. Probability of moving to another location. Renters only. Balanced sample.

	County	State
Neg. shock (cty/st) × HP growth < 0%	–0.11	0.00
	(–1.17)	(0.02)
Pos. shock (cty/st) × HP growth < 0%	–0.14	–0.02
	(–1.39)	(–0.25)
Neg. shock (cty/st) × HP growth > 0%	–0.27***	–0.03
	(–4.03)	(–0.57)
Pos. shock (cty/st) × HP growth > 0%	excluded	excluded
	group	group
Foreclosure dummy	0.56	0.10
	(1.14)	(0.28)
Log per capita inc. (cty/st)	1.92***	2.22
	(6.68)	(1.37)
Log population (cty/st)	–0.35***	–11.36***
	(–7.28)	(–5.39)
Age	–1.22***	–0.51***
	(–9.85)	(–3.85)
Age sq./100	0.79***	0.37***
	(5.96)	(3.22)
Log score	2.15***	2.66***
	(4.93)	(7.04)
N	418944	419433

Note: 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 county or state 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 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% (6%). Additional 3% selling cost for non-local moves.
	Foreclosure: income (house) one-time cost 20% (5%).
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. Owners, Aged 25–60

House Price Growth	All	Employed	Unemployed
	All moves		
HP growth $\leq 0\%$	0.142	0.131	0.371
HP growth $> 0\%$	0.157	0.147	0.379
Total	0.147	0.137	0.374
	Non-local moves		
HP growth $\leq 0\%$	0.018	0.007	0.267
HP growth $> 0\%$	0.018	0.007	0.244
Total	0.018	0.007	0.259

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

	OLS		Fixed Effects	
	Local Move	Non-Local Move	Local Move	Non-Local Move
	(1)	(2)	(3)	(4)
Unemployed × equity < 0%	–7.36***	22.44***	–3.17**	21.40***
	(–5.76)	(11.99)	(–2.41)	(11.10)
Employed × equity < 0%	0.83***	0.42***	1.36***	0.51**
	(3.38)	(2.79)	(3.61)	(2.52)
Unemployed × equity [0, 25]%	0.26	26.75***	2.77***	23.42***
	(0.42)	(19.37)	(3.84)	(17.40)
Employed × equity [0, 25]%	excluded group	excluded group	excluded group	excluded group
Unemployed × equity > 25%	6.92***	25.90***	9.90***	24.56***
	(20.22)	(56.39)	(20.30)	(52.15)
Employed × equity > 25%	8.63***	0.61***	7.09***	0.58***
	(66.19)	(14.35)	(25.66)	(5.25)
Age	–2.98***	–0.02	–2.20***	0.14
	(–27.19)	(–0.40)	(–4.98)	(0.84)
Age square/100	3.04***	0.00	1.61***	0.00
	(27.16)	(0.05)	(3.41)	(0.01)
Log income	–0.62***	0.11***	1.70***	0.23***
	(–6.44)	(2.73)	(9.01)	(3.23)
Foreclosed (last 24 months)	91.45***	4.11***	88.94***	4.41***
	(312.86)	(15.06)	(194.05)	(12.72)
Adj. R sq.	0.188	0.154	0.138	0.143
N	248387	248387	248387	248387

Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the regression $P(M_{it}) = \alpha + X_{it-1}\beta + u_{it}$, 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 regressors listed in the first column of the table. In columns (3)-(4), the equation estimated is $P(M_{it}) = X_{it-1}\beta + \mu_t + \nu_i + u_{it}$ where μ_t and ν_i are time and individual fixed effects, respectively. *** (**) [*] significant at the 1 (5) [10]% level. Standard errors are clustered by individual.

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

	Local Move (1)	Non-Local Move (2)
Unemployed × HP growth ≤ 0	–7.51***	25.89***
	(–21.66)	(49.06)
Unemployed × HP growth > 0	–1.26**	23.72***
	(–2.24)	(33.64)
Employed × HP growth ≤ 0	–5.45***	–0.22***
	(–43.41)	(–6.40)
Employed × HP growth > 0	excluded	excluded
	group	group
Age	–3.25***	–0.03
	(–29.86)	(–0.78)
Age square/100	3.46***	0.03
	(31.20)	(0.64)
Log income	–0.93***	0.09**
	(–9.71)	(2.25)
Foreclosed (past 24 months)	87.10***	3.84***
	(315.29)	(14.42)
Adj. R sq.	0.187	0.154
N	248387	248387

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 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. Different Region Types. Owners Aged 25–60

	Local Move (1)	Non-Local Move (2)
Local Weak × equity $< 0\%$	–0.49**	1.50***
	(–2.10)	(7.35)
Local Strong × equity $< 0\%$	0.02	0.61***
	(0.10)	(3.55)
Local Weak × equity $[0, 25]\%$	–0.25*	0.60***
	(–1.86)	(6.91)
Local Strong × equity $[0, 25]\%$	excluded group	excluded group
Local Weak × equity $> 25\%$	7.79***	1.50***
	(65.99)	(24.13)
Local Strong ×Equity $> 25\%$	8.29***	0.72***
	(70.00)	(12.13)
Ages below 30, fraction	18.63***	1.02***
	(32.81)	(4.89)
Ages above 55, fraction	1.36***	–0.04
	(14.39)	(–0.94)
Log per capita area income	18.25***	1.86
	(4.60)	(0.99)
Foreclosed (last 24 months)	91.62***	3.92***
	(439.84)	(19.85)
Adj. R sq.	0.186	0.003
N	495473	495473

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 regressors listed in the first column of the table. *** (**) [*] significant at the 1 (5) [10]% level. Standard errors are clustered by individual. We simulate two kinds of regions: weak local regions and strong local regions differ on the intensity of local versus non-local job offers (60 percent and 80 percent, respectively).

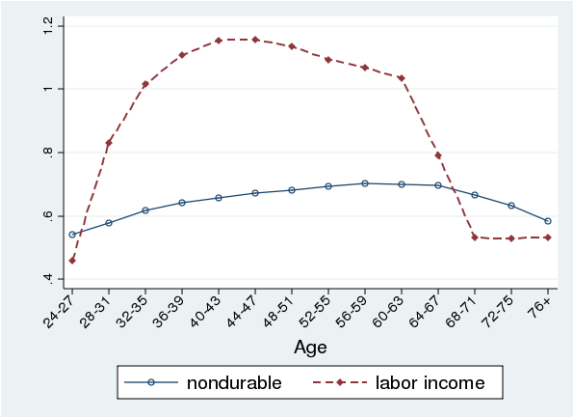
Table 14: Moving in the Model. Appreciation-Depreciation. Different Region Types. Owners Aged 25–60

	Local Move (1)	Non-Local Move (2)
Weak Local × HP growth ≤ 0	–5.96***	0.69***
	(–48.59)	(12.77)
Weak Local × HP growth > 0	–0.57***	0.70***
	(–3.86)	(11.28)
Strong Local × HP growth ≤ 0	–5.58***	–0.11**
	(–45.70)	(–2.31)
Strong Local × HP growth > 0	excluded	excluded
	group	group
Age	–3.33***	–0.11***
	(–43.58)	(–3.42)
Age square/100	3.55***	0.12***
	(45.56)	(3.65)
Log per capita area income	31.40***	1.87
	(7.94)	(0.99)
Foreclosed (last 24 months)	87.05***	3.73***
	(441.91)	(19.55)
Adj. R sq.	0.185	0.003
N	495473	495473

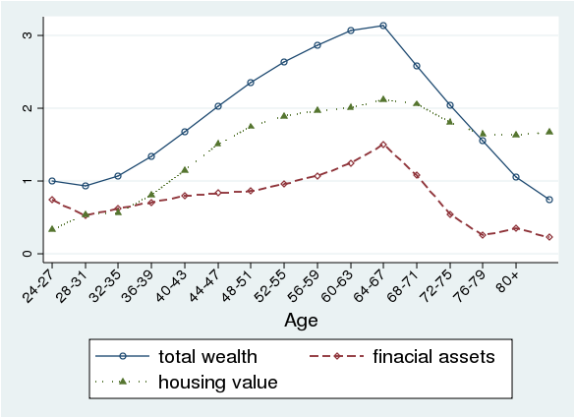
Notes: The table shows estimated coefficients (and t-statistics in parentheses) from the equation $P(M_{it}) = \alpha + X_{it-1}\beta + u_{it}$, where M_{it} is an indicator variable that equals 100 if individual i moves between period $t-1$ and t, zero otherwise, and X is a vector of regressors listed in the first column of the table. *** (**) [*] significant at the 1 (5) [10]% level. Standard errors are clustered by individual. We simulate two kinds of regions: weak local regions and strong local regions differ on the intensity of local versus non-local job offers (60 percent and 80 percent, respectively).

FIGURE 1: LIFE-CYCLE PROFILES. THE BENCHMARK CASE

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



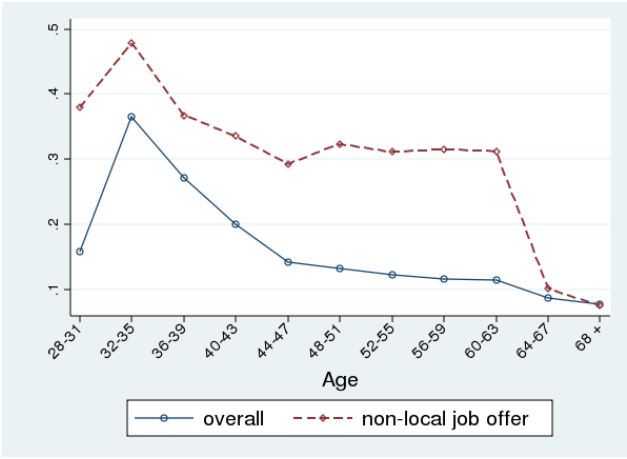
(a) Income and Consumption



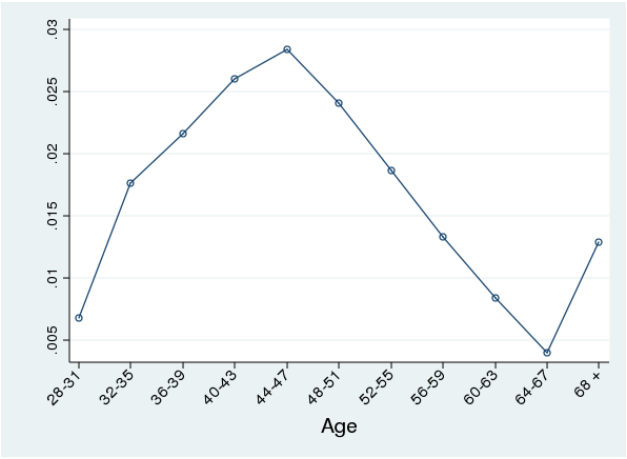
(b) Wealth

Figure 2: The Benchmark and the Data

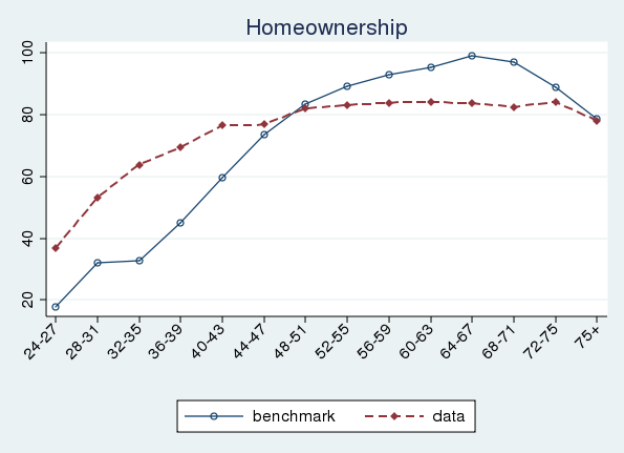
(Data for homeownership, wealth and earnings from the Survey of Consumer Finances, averages from 1989–2004. Data on moving rates and foreclosure from Equifax)



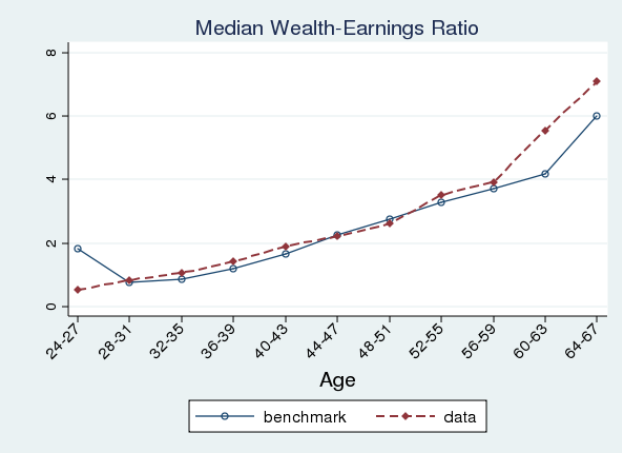
(a) Overall moving rates

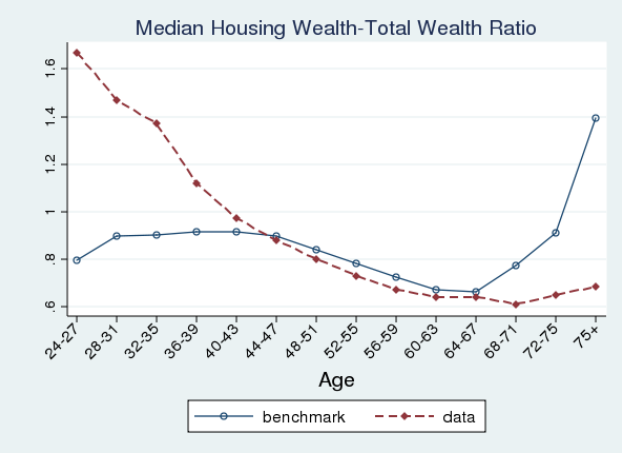


(b) Foreclosure rate (out of total households)



(c) Homeownership





(d) Wealth and Earnings