House Prices, Mortgage Debt, and Labor Mobility

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Abstract

Using detailed credit and employment data for the United States, we estimate the effect of mortgage debt on labor mobility. We find a robust negative relation between the loan-to-value ratio (LTV) of the primary residence and labor mobility. Individuals with negative home equity are 3.6 percentage points less likely to move in a year. This effect is stronger for sub-prime and liquidity-constrained borrowers. We also find that diminished labor mobility owing to higher LTVs depresses labor income growth, especially for individuals with less access to liquidity and longer tenure in their current job. Consistent with a housing-lock explanation, we find that individuals with higher LTVs have higher intra-ZIPcode job mobility. Overall we document significant spillover from the housing market to the labor market.

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Introduction

The great recession has heightened interest in understanding how house prices affect individual consumption and investment behavior. Answering this question is complicated by the fact that houses are financed with leverage and thus changes in house prices affect both household wealth and leverage. For example, the steep fall in house prices during the great recession reduced home values to below the outstanding mortgage loan for many households. i.e., the mortgage was underwater. Such extreme leverage can affect many aspects of household behavior. It can affect their incentives to pay their mortgage (Ghent and Kudlyak [2011]), invest in their house (Melzer [Forthcoming]), and work to improve their labor income (Bernstein [2016]). In this paper we focus on how house prices affect job mobility. Specifically we want to understand the extent to which labor mobility gets affected when home values are less than the outstanding mortgage debt.

Mortgage debt – when extreme – can affect labor mobility if an individual is credit constrained and if there are some (perceived) costs of renting a house (Stein [1995], Ortalo-Magne and Rady [2006]). If a house is underwater, a home owner facing the prospect of moving can do one of two things. She can sell her house and compensate the bank for the shortfall between the sale price and mortgage outstanding. Her ability to do this will depend on the availability of liquidity and the extent to which she is credit constrained. Alternatively she can retain the house and possibly rent it.[1] If the individual perceives a cost to renting the house and if she is credit constrained then she may be willing to give up some attractive employment opportunities to remain in her residence. We use detailed credit profile and employment data of a large sample of individuals to estimate the effect of mortgage debt on labor mobility.

Our empirical analysis leverages a novel dataset on individual credit profiles and employment history. The anonymized data comes from Equifax Inc., one of the three major credit bureaus. Equifax Inc. is a global leader in information solutions, and is involved in the col-

[1] The third option is to default on the mortgage and walk away. This option has obvious costs in terms of lower future credit access. We discuss this in greater detail in Section 5.2.

lection and transmission of data on the credit histories and employment of individuals within the United States. The credit data includes anonymized information on the credit histories of all individuals in the U.S., including historical information on all their credit accounts, credit scores, and ZIP-codes of residence. The employment data covers millions of employees across the U.S. from over 5,000 firms and includes anonymized information on the employee's wages, job tenure, and firm level details. This is one of the first papers to use such detailed credit and employment data on the US population.

We use the credit and employment data to construct multiple measures of job mobility. Our main measure uses the credit data to identify instances when the individual moves from one ZIPcode to another. Next, we use the employment data to differentiate between mobility within the same firm and mobility across firms. These measures help us understand the extent to which firms may help their new employees (with underwater mortgages) to overcome credit constraints (for e.g. through relocation allowances). We also identify job mobility that does not involve geographic mobility. To the extent mortgage debt affects geographic mobility, it may affect an individual's incentive to search for jobs within her local area. Finally we also distinguish mobility not associated with a mortgage default from mobility induced by delinquency.

We measure the amount of mortgage debt by the loan to value ratio (LTV) on the primary residence. LTV is the ratio of total mortgage loan outstanding over the imputed market value of the house. We aggregate the outstanding balance on both the primary morgage and home equity lines of credit to measure loan outstanding. We use house price index at the ZIPcode level to capture house price changes. Since we expect LTV to have a non-linear effect on mobility, our main independent variables include a set of five dummy variables that identify individuals with LTVs in different buckets

Ordinary least squares estimates of the effect of LTV on labor mobility are likely to be biased due to several factors. For example, an individual's loan outstanding can change both due to normal loan repayment and also due to prepayments.[2] To the extent partial prepayment is

[2]We treat refinancing as closing of one loan account and the opening of another and hence refinancing will not alter LTV in our sample.

an endogenous decision, it may be correlated with the individual's decision to move and thus bias our estimates. To account for such factors, we follow Bernstein [2016] and implement an instrumental variable (IV) specification wherein we construct a synthetic LTV (SLTV) based on the ZIPcode level house price changes and a hypothetical loan repayment schedule. All our specifications include ZIPcode-by-month and purchase cohort-by-month fixed effects to control for local economic conditions and life cycle effects. This methodology compares mobility across individuals living in same ZIPcodes who have different LTVs because they belong to different purchase cohorts after controling for average cohort effects.

We find a strong negative relation between LTV and job mobility with both OLS and IV specifications. Individuals with higher LTVs are less likely to move from their current ZIPcode. We find that this effect is present both for mobility within the same firm and for mobility across firms. Our estimates are economically significant. As compared to individuals with *LTV* between 0.7 and 0.8, individuals with LTV between 1 and 1.4 are 0.3% less likely to move in a month. In comparison, the mean mobility of the individuals in our sample is 0.6% per month. Our empirical specification includes individual fixed effects to control for time-invariant individual characteristics that may be correlated with mobility. We also include within-ZIPcode time effects to control for local economic conditions and within-purchase cohort time effects to control for lifecycle effects that may affect mobility. We are able to estimate this strict specification because house prices and time in the house have a multiplicative effect on LTV.

Underwater mortgages will affect labor mobility especially if the individual is credit constrained. Such individuals may not be able to bridge the shortfall between the mortgage outstanding and the home value. Using credit scores and access to liquidity as alternate measures of credit constraints, we find that the negative effect of LTV on labor mobility is stronger for subprime borrowers and for those with below median undrawn credit limit relative to the mortgage outstanding. This offers strong evidence consistent with credit constraints being an important factor in explaining the negative relation between home LTV and mobility.

Too much debt relative to the value of the house may also encourage individuals to default on their morgage. We find that the probability of mortgage delinquency does indeed increase with LTV. Since delinquency is likely to result in the individual moving out of her house, the effect of LTV on delinquency is likely to bias our baseline estimates of mobility downward. We find that this in indeed the case. When we focus on mobility not associated with a delinquency, we find that LTV has an economically larger effect on mobility. As compared to individuals with *LTV* between 0.7 and 0.8, individuals with LTV between 1 and 1.4 are 0.4% less likely to experience a non-delinquent mobility in a month. In comparison, the mean non-delinquent mobility of the individuals in our sample is 0.4% per month.

When individuals forego attractive job opportunities because of an inability (read reluctance) to move, they are likely to remain longer in jobs that pay lower wages and provide fewer opportunities for career progression. Consistent with this, we find that individuals with higher LTVs have lower income and a lower likelihood of being promoted. LTV has an incrementally stronger negative effect on income and likelihood of job promotion for borrowers with less access to liquidity as compared to those with more access to liquidity. We also find that the negative relation between LTV and income is stronger for borrowers that have spent more than two years on their job. These cross-sectional results help establish that constrained mobility may be an important reason for the observed negative relationship between LTV and labor mobility.

Individuals with high levels of mortgage debt who are geographically constrained may be more inclined to look for employment opportunities within the same region. Consistent with this, we find that individuals with higher LTVs have higher intra-ZIPcode job mobility.

Summarizing, our analysis documents significant spillover effects from the housing market to the labor market. Individuals with home LTV greater than one are significantly less likely to move residence as compared to individuals with moderate LTVs. This effect is present for both intra-firm and inter-firm job mobility and is stronger for individuals that are credit constrained and have lower access to liquidity. Higher LTV depresses labor income and the likelihood of job promotion and is associated with a greater intra-ZIPcode job mobility.

Our sample consists of a panel with credit and employment information over the 72 month period between 2010-2015. We focus on homeowners as of January 1, 2010, whose mortgages were originated sometime before Jan 1, 2010. From this set of homeowners we randomly select a sample of 300,000 individuals and conduct our analysis. This allows us to keep our computations feasible. Our final sample is a individual-month panel with over 13 million observations.

Although our dataset is large by any measure, we make note of two potential issues that may affect our estimates. First, our employment data is not comprehensive and is more likely to include individuals employed in large firms. To account for this, we conduct some of our analysis only with the credit data and compare our estimates across the samples. Second, by construction our sample only includes individuals who are current on their mortgage as of Jan 2010. Depending on when they bought their house, some of them may have gone through the crisis without defaulting on their mortgage. Thus on average, the individuals in our sample may have a lower propensity to default on their mortgage.

Our paper makes a number of important contributions. Ours is the first paper to use detailed credit and employment data to do a comprehensive study of the effect of mortgage debt on mobility. We show that house prices affect all aspects of labor mobility. The negative spillover effects from the housing market to the labor market that we document should be considered by policy makers when faced with future house price declines. Our results may also contribute in explaining the slow recovery in employment following the house price decline during the great recession. Further, they also have relevance for companies interested in retaining and developing human talent. We show that credit constraints may be an important factor that affect an employee's willingness to move to take up new challenges, which calls for more proactive policies on the part of companies to help such employees relocate.

The rest of the paper is organized as follows. In the next section we outline the papers that are related to our work. Section 2 develops the hypothesis while Section 3 outlines our empirical methodology. In Section 4, we describe our data. Section 5 presents our empirical results while Section 7 concludes.

1 Related Literature

Although a number of prior studies examine the relation between home equity and labor mobility, a consensus remains elusive. While Chan [2001], Ferreira et al. [2010], Henley [1998], and Modestino and Dennett [2013] document a positive relation between home equity and labor mobility, Schulhofer-Wohl [2012] and Coulson and Grieco [2013] document the opposite.[3] A key factor explaining the lack of consensus is data limitations. For example, Chan [2001] uses mortgage data from a single bank and cannot differentiate between instances of refinancing and job mobility. Ferreira et al. [2010] use data from the American Housing Survey (AHS). The AHS follows homes and not households, and hence the authors are limited in their ability to cleanly identify labor mobility[4]. In contrast, our paper uses a granular administrative dataset on the credit and employment outcomes of millions of individuals across the U.S.. This dataset allows us to identify both home equity and labor mobility with a high degree of accuracy.

Our study is most closely related to two recent papers on home equity and labor mobility: Demyanyk et al. [Forthcoming] and Bernstein and Struyven [2016]. Using a sample of mostly subprime borrowers, Demyanyk et al. [Forthcoming] document a negative association between home equity and labor mobility. The authors argue that this relation arises because individuals with low home equity experience larger utility gains from accepting higher paying out-of-region job offers than their (otherwise identical) high home equity peers. In contrast, our study uses a sample of both prime and subprime borrowers and finds that individuals with low equity are less likely to move across regions (e.g. a positive relation) but more likely to move to jobs without moving residence. As we document, there are systematic differences between prime and subprime borrowers in their propensity to default on their mortgage when home equity is low. Moreover, we observe much richer employment data than Demyanyk et al. [Forthcoming] which allows us to additionally identify the effect of home equity on different types of mobility:

[3]Other related work studies different aspects of mobility and documents nuanced results. For instance, Donovan and Schnure [2011] find that negative equity reduces intra-county migration but leaves out-of-state migration unaffected, Molloy et al. [2011] find no correlation while Nenov [2012] document that negative equity reduces in-migration rates, but has no impact on out-migration.

[4]Home equity is also self-reported in the AHS

e.g inter- versus intra-firm mobility, intra- versus intra-regional mobility, and also the effect of home equity on labor income. We find that lower home equity results in lower inter- and intra-firm mobility, lower labor income, and higher intra-regional mobility - all of which are consistent with home equity constraining geographic mobility.

In contrast to Demyanyk et al. [Forthcoming], Bernstein and Struyven [2016] use administrative data from the Netherlands, a country where mortgages are full recourse, and find a positive association between home equity and labor mobility. We find a similar result in the U.S. where mortgages are non-recourse in many states. In non-recourse markets, borrowers may be tempted to walk away from their mortgage at high LTVs (Ghent and Kudlyak [2011]). While we find some evidence for an increase in default at higher LTVs, overall we find that negative home equity reduces mobility.

Finally, our paper is also related to a recent body of work that investigates how households respond to extreme leverage. Prior studies have examined the effect of extreme leverage on entreprenuerial activity (Adelino et al. [2015]), employment oppourtunities (Bos et al. [2015]), labor income (Debbie and Song [2015]), and household consumption and investment decisions (Bhutta et al. [2010], Cunningham and Reed [2013], Foote et al. [2008], Fuster and Willen [2013], Guiso et al. [2013], Mian et al. [2013]). Melzer [Forthcoming] finds that households with negative home equity reduce investments in their house, since they anticipate not to be residual claimants any more. Bernstein [2016] argues that households reduce their labor supply in response to negative home equity and income based mortgage assistance programs. Using administrative data from home affordable modification programs, Scharlemann and Shore [2016] find that individuals with negative home equity are more likely to default on their mortgage. We contribute to this literature by documenting that negative home equity adversely affects labor mobility and impedes career progression.

2 Hypothesis development

Lower levels of home equity can negatively affect labor mobility if individuals are credit constrained (Stein [1995], Ortalo-Magne and Rady [2006]). The basic intuition relies on the fact that mortgage lending requires large downpayments, and that nominal price decreases and higher home LTVs burden homeowners via capital losses. Credit constraints thenlimit the ability of a borrower to make-good on short-falls between the mortgage outstanding and the house price, and hence constrain household mobility when LTV is high (e.g. household "lock-in" effects)[5]. The credit constraint channelthus predicts (1) a negative relation between home LTV and labor mobility (especially when LTV is above one) and (2) that this relation is differentially stronger for households that are more constrained and have lower access to liquidity.

Lower levels of home equity can also negatively affect labor mobility if individuals exhibit nominal loss aversion (Genesove and Mayer [2001], Engelhardt [2003], Annenberg [2011]). For example, individuals that are "underwater" on their mortgages may be reluctant to change residences because they value gains and losses differently - such as in prospect theory (Kahneman and Tversky [1979]). These individuals may either set unrealistically high prices for their homes or wait until a positive housing shock to change their residence, both of which would reduce their labor mobiliity. While we cannot distinctively rule this channel out, our results are generally more consistent with credit constraints being the dominant effect.

Finally, when mortgages are non-recourse (such as in several U.S. states), lower levels of home equity can positively affect labor mobility through the incentives for strategic default. All else equal, this would predict a positive association between home LTV and labor mobility (Ghent and Kudlyak [2011], Deng et al. [2000]). Since our main results document a negative relation between home LTV and labor mobility, we are able to rule out strategic default as the primary driver of labor mobility. However, we do find evidence of a positive relation between home LTV and labor mobility among the subsample of (eventually) delinquent borrowers. This prevents us from ruling out strategic default as a factor in mobility decisions.

[5]Stein [1995] shows that this result holds in his model even if households have the option of renting their homes.

We also note that home equity may affect indiviuals in ways that are non-exclusive to any of the above channels. First, if individuals forego attractive job opportunities due to their inability to move, then lower levels of home equity may hinder career progression. This in turn would predict that high LTV individuals may be in jobs that pay less and offer less opportunities for growth and promotion. Second, firms may be willing to help their employees overcome credit constraints or loss aversion if moving the employee to a different location is valuable for the firm. We differentiate between intra- and inter-firm mobility to evaluate the merits of this claim.

3 Empirical Methodology

To evaluate the effect of mortgage debt on labor mobility, we begin by estimating variants of the following model:

$$y_{izt} = \delta_i + \delta_{zt} + \delta_{c(i)t} + \sum_k \beta_k \times 1_{\{l_k \leq LTV_{it} < h_k\}} + \gamma \times X_{it} + \epsilon_{izt} \tag{1}$$

where the dependent variable y_{izt} is a dummy variable that identifies if individual i in ZIP code z moves their residence in year-month t. Our primary measure of household mobility is the dummy variable *Mobility*, which takes a value of one in year-month t if the ZIP code associated with individual i's primary residence in month $t+1$ is different from their current ZIP code in month t, or an individual becomes delinquent on a mortgage in month t. We classify delinquency as the first instance an individual is late on mortgage payment by more than 90 days (See Rajan et al. [2015])[6]. The *Mobility* variable includes delinquency to reflect mobility induced by default. Note that while *Mobility* requires that an individual owns a house prior to movement (or default), it does not require an individual to either own a house in their new ZIP code or to have sold their house in the previous ZIP code. Instead, we only require that the individual changes the ZIP code of primary residence in their credit profile[7].

[6]We code delinquency as one at the begining of the 90 day period (i.e. 3 months before the individual is 90 day late on payments) to reflect when the decision to become delinquent was made.

[7]In unreported results we find that our results are robust to defining *Mobility* at the MSA level.

Our employment data allows us to distinguish between instances of *Mobility* where an individual moves ZIP codes and continues to be employed in the same firm ($Intra-Firm\ Mobility$), and instances where an individual moves ZIP codes and ceases to be employed with their current employer ($Inter-Firm\ Mobility$). We also distinguish between mobility associated with mortgage default (*Delinquency)* and mobility that is not associated with mortgage default (*Non-Delinquent Mobility)*. Specifically, we define *Delinquency* as a dummy variable that takes a value of one in year-month t if the individual becomes 90 days late on mortgage payments for the first time in year-month $t+3$. *Non-Delinquent Mobility* is a dummy variable that takes a value of one if *Mobility* is equal to one and *Delinquency* takes a value of zero.

The main independent variables in our analysis are the indicator functions $\left\{1_{\{l_k \leq LTV_{it} < h_k\}}\right\}_k$ which equal one when individual i's loan-to-value ratio at the end of year-month t (LTV_{it}) is between l_k and h_k - i.e., $LTV_{it} \in [l_k, h_k)$.[8] We calculate LTV using the imputation method described in Bernstein [2016]. Before we describe the construction of the indicator functions, we describe our calculation of LTV. While we observe the exact loan amount outstanding at any point in time and changes in house prices at the zipcode level, we do not observe individual home values at the time of initial purchase (or refinance). Hence we make some simplifying assumptions to calculate LTV. We assume that LTV at the time of origination (refinancing) is 0.7 for all mortgages. The basis for this assumption is two-fold. First, as documented by Bernstein (2016) the median LTV at the time of origination for mortgages on houses purchased during 2010-2014 is close to 0.7. Second, we find that this is also the case in a smaller property dataset maintained by Equifax Inc. This dataset contains values for 90% of the properties in the U.S. collected from property tax assessors for the years 2013-2015. The median LTV at origination for mortgages on residential properties purchased in 2013-14 is 0.72[9]

We also assume that the change in house prices is symmetric across all houses within each ZIP code at any point in time t. Therefore, LTV is calculated as the ratio of the actual loan

[8]The loan-to-value ratio is computed on the individual's primary residence as reported in our credit data.

[9]We don't use this data to calculate LTVs at origination in our sample because its coverage is limited to 2013-2014.

amount and changes in ZIP code level house price indices:

$$LTV_{it} = LTV_o \times \frac{(1 + \%\Delta Loan_{it})}{(1 + \%\Delta HPI_{zt})}, \tag{2}$$

where LTV_o is the LTV at loan origination or refinancing (0.7 in our case), $\%\Delta Loan_{it}$ is the percentage change in loan amount outstanding since origination, and $\%\Delta HPI_{zt}$ is the percentage change in the ZIP code level house price index since origination. Note that both home price changes and initial LTV's are likely to differ from those in our assumptions. This may be a concern if the measurement error between the true LTV and our calculated values are systematically correlated with labor mobility (e.g. good quality individuals make larger downpayments, have lower LTVs, and are more likely to get better job offers and move their residence). We argue that high-dimensional fixed effects and instrumental variables specifications detailed below help in mitigating these concerns.

We divide the range of LTVs in our sample into five non-overlapping buckets: $(0, 0.7]$, $(0.7, 0.8]$, $(0.8, 1]$, $(1, 1.4]$, and (> 1.4). We then include indicator functions to represent these buckets excluding the (0.7, 0.8] bucket. This represents the base case in our regressions. The coefficient β_k in Equation 1 is a measure of the difference in the average mobility of individuals with LTV between l_k and h_k as compared to individuals with LTV between 0.7 and 0.8. We also include a separate dummy variable that identifies individuals with LTV exactly equal to zero. Note that we employ dummy variables instead of a linear term in LTV because we expect the effect of LTV on mobility to be non-linear, especially around $LTV = 1$.

We include a robust set of controls to ensure ensure that our estimates are not biased. First, we include individual fixed effects (δ_i) to control for individual-level time-invariant characteristics. Second, we include ZIP code specific time effects (δ_{zt}) to account for time-varying local economic conditions that could affect both LTV and labor mobility. For example, adverse local economic conditions may decrease home values, increase LTVs, and increase the likelihood of labor mobility (e.g. moving to an economically better area). Third, we include purchase cohort specific time effect ($\delta_{c(i),t}$) to control for time-varying life cycle and purhcase effects. For instance, individuals who who just purhcased a home in a new neighborhood may be less likely to move immediately and also have (mechanically) higher LTVs. Together $\delta_{c(i),t}$ and δ_{zt} control for both the average mobility within a cohort and the average mobility in a ZIPcode at a particular point in time. Finally, we include a quadratic term in job tenure $(X_{i,t})$ to account for time-varying individual-level changes in the propensity to move.

Two main factors drive the variation in LTV_{it} in our sample: the outstanding loan amount and ZIP code level house prices. These factors have a multiplicative effect, which ensures that we have variation in LTV across individuals within the same ZIPcode as well as variation in LTV across individuals within the same purchase cohort.

Outstanding loan amounts can change either from scheduled loan repayments over time or from partial prepayments. Therefore, to the extent that prepayments are endogeneous decisions related to the decision to move, our OLS estimates would be unlikely to capture the causal effect of LTV on labor mobility. For example, an individual who experiences a severe life event such as a divorce may decide to prepay their mortgage in full and move their residence. Individuals who secure high paying jobs in other areas may also pre-pay their mortgage before their departure. We control for such endogenous changes in loan amounts by isolating the variation in LTV due to regional variation in house prices. Specifically, we follow Bernstein [2016] and instrument LTV with a synthetic loan-to-value ratio $(SLTV)$. $SLTV$ is calculated by assuming that monthly loan payments are equal to those that would arise under a 30-year mortgage with a fixed interest rate and no prepayment. The synthetic change in loan amount every month is given by:

$$\%\Delta SynthLoan_{ct} = -\frac{(1+r)^{t-c}-1}{(1+r)^{360}-1}, \tag{3}$$

where r is the mortgage interest rate. We assume that the mortgage interest rate is 6.75% - the median mortgage interest rate in our sample. The synthetic change in loan amount is independent of an individual's decision to pre-pay their mortgage. Finally, using the synthetic loan amount, we calculate $SLTV$ as:

$$SLTV_{it} = LTV_o \times \frac{(1 + \%\Delta SynthLoan_{ct})}{(1 + \%\Delta HPI_{zct})} \tag{4}$$

We employ $SLTV$ as an instrument for LTV in the following instrumental variables (IV) regression:

$$1_{\{l_k \leq LTV_{it} < h_k\}} = \delta_i + \delta_{zt} + \delta_{c(i)t} + \sum_k \theta_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} + X_{it}\gamma + \epsilon_{izt} \quad \forall k$$

$$y_{izt} = \delta_i + \delta_{zt} + \delta_{c(i)t} + \sum_k \beta_k \times 1_{\{\widehat{l_k \leq LTV_{it} < h_k}\}} + X_{it}\gamma + \epsilon_{izt}, \tag{5}$$

where the $SLTV$ bucket indicator functions, $1_{\{l_k \leq SLTV_{it} < h_k\}}$, are used as instruments for the corresponding LTV bucket indicator functions. We thus have five first stage regressions, one for each of the LTV bucket indicator functions. Similar to LTV, the variation in $SLTV$ is driven by changes in loan amount and changes in house prices. The difference between $SLTV$ and LTV is that $SLTV$ uses only changes in loan amounts that are only a function of the time since the house was purchased or the purchase cohort to which the individual belongs. All fixed effects from the OLS specification in Equation 1 are included in the IV specification.

4 Data

4.1 Sample Construction

Our empirical analysis leverages anonymized data on individual credit profiles and employment information from Equifax Inc., one of the three major credit bureaus. Equifax Inc. is a global leader in information solutions, and is involved in the collection and transmission of data on credit histories and employment for individuals within the United States. This is one of the first papers to use such detailed credit and employment data on the US population.

The anonymized credit data contains information on the credit histories for all individuals with a credit history in the U.S for the period between 2010-2016. This includes anonymous information on historical credit scores along with disagreggated individual credit-account level information such as account type (e.g. credit card, home loan, etc.), borrower location, account age, total borrowing, account balance, and any missed or late payments. The employment data covers millions of individuals from more than 5,000 employers in the U.S. and includes anonymous information on each each employee's wages, salary, bonus, average hours worked, job tenure, firm level details, and whether the employee remains employed at the firm at a given point in time.

We merge these two datasets to obtain a panel with credit and employment information over the 72 month period between 2010-2015. We restrict the panel to homeowners with an active mortgage loan as of January 1, 2010. Note that these mortgages were originated sometime before January 1, 2010. While the earliest mortgage in our sample was originated in 1976, most of the mortgages were originated during the boom years of 2002-06. To make the computations feasible, we draw a random sample of 300,000 individuals from this sample to conduct our analysis.

We retain individuals in our sample until the first time they move their residence. Thus, if an individual changes the ZIP code of their residence for the first time in January 2012, they are dropped from the sample starting February 2012. We also drop individuals after they become delinquent on their mortgage. Refinancing is reflected in our data by the closing of one account and the opening of a new account. In such instances, we retain the old account up until the month before its closure and then switch to the new account with a beginning LTV of 0.70 from the month of refinancing.

The ZIPcode level house price data used in our analysis comes from Corelogic and covers the period 1976-2015. Specifically, we use Corelogic's monthly house price indexes (HPI) to impute changes in home values at the ZIP code level. These indexes are calculated using a weighted repeat sales methodology and are normalized by setting the index value as of January, 2010 to 100.

We make note of two issues with our sample that may potentially bias our estimates. First, our sample is confined to the individuals in the intersection of the credit and employment data. Thus, our sample may not be representative of the population of mortgage borrowers in the U.S. To alleviate these concerns, in Section 5.2 we repeat our baseline estimates with a random sample of individuals from the more comprehensive credit data and find no differences in the main results. While we are able to implement our baseline tests using just the credit data, the employment data allows us to distinguish between mobility within- and across firms and also estimate the effect of home equity on labor income.

Second, our sample may be subject to a survivorship bias. Recall that we focus on individuals who are current on their mortgage as of January, 2010. Depending on when they bought their house, these individuals may have gone through the crisis without defaulting on their mortgage even if their house was underwater. Thus, on average, the individuals in our sample may have a lower propensity to default on their mortgage.

4.2 Sample Description & Statistics

Figure 1 compares the distribution of individuals in our sample across states in the U.S. to the same distribution of entire population (as of 2010) based on location of an individual's residence. The numbers in the figure represent the percentage difference in this distribution, i.e. $\frac{SamplePopulation_s}{TotalPopulation_s} - \frac{SamplePopulation}{TotalPopulation}$. The distribution of employees across states in our sample is comparable to the distribution of the U.S. population for most states. The difference lies in Nevada, Colorado, Nebraska, Missouri and Minnesota which appears to be over represented while Montana, Wyoming, Vermont and West Virginia are over-represented[10].

Table 1 reports summary statistics for the key variables that used in our analysis. We have a total of 13,389,609 individual-month observations. The top panel reports summary statistics for our outcome variables. The average probability that an individual moves in our sample is 0.6% per month[11]. This is comparable to prior literature which finds the average mobility to be

[10] In ureported tests, we find that our results are robust to excluding these states.

[11] As mentioned before, we classify an individual as having moved in month t if their ZIP code in month *t+1* is different from their ZIP code in month t, or if the individual becomes delinquent in month $t + 1$.

6.63% per year (Demyanyk et al. [Forthcoming]). We find that about two-thirds of the mobility in our sample is due to *Intra-firm Mobility* intra-firm and one-third is due to *Inter-firm Mobility*. The average monthly delinquency rate in our sample is 0.2%. Hence, two thirds of the mobility in our sample (0.4%) is not associated with delinquency.

The bottom panel of Table 1 summarizes our independent variables. The mean (median) loan size in our sample is $170,376 ($140,000). Loan size is highly right skewed and has a maximum value exceeding $3 million. The purchase price is imputed from the original loan amount at origination and our assumption that LTV at origination is equal to 0.7. The average loan balance in our sample is $130,832, about 74.4% of the original loan amount.

Home values are calcuated using the imputed purchase price and subsequent ZIP ode level price changes. We find that the mean (median) LTV and $SLTV$ in our sample are 0.5 (0.6) and 0.7 (0.7), respectively. From the summary statistics for the indicator functions, we find that 5% of the observations in our sample have LTV equal to zero. We also find that about 90% of the observations in our sample have an LTV between 0 and 1. Of the individuals with LTV between 0 and 1, 60% have an LTV less than 0.7, 20% have an LTV between 0.7 and 0.8, and 10% have an LTV between 0.8 and 1. Roughly 5% of our observations have an LTV greater than 1. Recall that since we estimate LTV with noise, the actual number of individuals who perceive their house to be underwater may be higher or lower than 5%.

Figure 2 displays the density plot for the number of loan originations across time. Consistent with the spike in mortgage originations in the early 2000s, most individuals in our sample originate loans between 2002-2006. Hence, the individuals in our sample are likely to have experienced a decline in house prices during the Great Recession.

Panel (a) of Figure 3 plots the distribution of monthlyhouse price changes between 2001-2015. Most monthly house price changes at the ZIPcode level fall within the range of -2.5% to 2.5%. These changes, when accumulated over several months, can amount to large innovations in house prices. Panel (b) illustrates this idea by plotting the density of annual house price changes. Annual house price changes range from -20% to +20% between 2001-2015. Combined, these plots highlight the existence of significant variation in house prices in our sample, and hence large variation in LTVs that will help identify our effects.

5 Empirical Results

5.1 Home Equity & Labor Mobility

We begin our empirical analysis by estimating equation (1) and present the results in Table 2. The dependent variable in column (1) is *Mobility* and we estimate the model excluding within cohort time effects. In this case the variation in LTV is driven by changes in loan amounts resulting from both normal loan repayments and prepayments. The positive and significant coefficient on $1_{\{0<LTV_{it}\leq 0.7\}}$ in column (1) indicates that individuals with $LTV \in (0, 0.7]$ are 0.1% more likely to move residence as compared to those with $LTV \in (0.7, 0.8]$, our base case. We also find that the coefficients on the other three indicator variables that identify individuals with LTVs progressively greater than 0.8 are negative and significant. Thus individuals with higher LTVs on average have lower mobility. It is interesting to note that the coefficients also progressively increase with LTV values. Compared to individuals with $LTV \in (0.7, 0.8]$, those with $LTV \in (0.8, 1]$, are 0.3% less likely to move while those with $LTV \in (1, 1.4]$, are 0.5% less likely to move. The individuals with the lowest mobility are those with LTV greater than 1.4, who are 0.9% less likely to move as compared to those with $LTV \in (0.7, 0.8]$.

In column (2) we repeat our estimates after including within-cohort time effects. The coefficient on $1_{\{0<LTV_{it}\leq 0.7\}}$ is identitical to that in column (1). The coefficient on $1_{\{0.8<LTV_{it}\leq 1\}}$ is now positive and marginally significant. Thus once we control for the average difference in mobility across cohorts, individuals with $LTV \in (0.8, 1]$ are more likely to move as compared to those with $LTV \in (0.7, 0.8]$. We find that the coefficients on indicator variables for LTV values greater than one continue to be negative and significant. Comparing the coefficients in column (2) to those in column (1) we find that the absolute value of the coefficients on both $1_{\{1<LTV_{it}\leq 1.4\}}$ and $1_{\{1.4\leq LTV_{it}\}}$, are smaller once we control for within cohort time effects. In particular, individuals

with $LTV \in (1, 1.4]$ and $LTV \in (> 1.4)$ are both 0.3% less likely to move respectively as compared to individuals with $LTV \in (0.7, 0.8]$. Even these magnitudes are economically very large when compared to the sample mean mobility of 0.6%.

In columns (3) - (4) we focus on intra-firm mobility. As mentioned before, we focus on intra-firm mobility to see if firms help individuals overcome credit constraints so as to be able to move even when their house is underwater. Our results indicate that this is not the case. Individuals with higher LTVs are less mobile even within their existing firm. Our results are again economically meaningful. From column (4) we find that individuals with $LTV \in (1, 1.4]$ have 0.1% lower intra-firm mobility as compared to individuals with $LTV \in (0.7, 0.8]$. In comparison the average intra-firm mobility in our sample is 0.4% per month. Finally in columns (5) - (6) we focus on inter-firm mobility and find that individuals with higher LTVs have lower inter-firm mobility. Due to fewer instances of inter-firm mobility in our sample (only about one-third of the mobility in our sample is across firms) our results are statistically less significant in column (6).

In Table 3, we present the results of the reduced form estimation wherein we include the indicator functions for SLTV instead of LTV. To reiterate, we calculate SLTV under the assumption that individuals pay down their mortgage as if it were a 30-year fixed rate mortgage. Thus the variation in SLTVs arise from the ZIPcode level house price changes and the timing of house purchase and these two have a multiplicative effect. In column (1) we estimate our model with both within-ZIPcode time effects and within-cohort time effects. Thus we control for the difference in average mobility both across cohorts and across ZIPcodes. We find that our results are very similar to those in column (2) of Table 2. While the coefficients on $1_{\{0<SLTV_{it}\leq 0.7\}}$ and $1_{\{0.8<SLTV_{it}\leq 1\}}$ are positive that on $1_{\{1<LTV_{it}\leq 1.4\}}$ and $1_{\{1.4\leq LTV_{it}\}}$, are negative and significant. Thus individuals with higher SLTVs have a lower mobility. Note that the coefficients in the reduced form estimation are an unscaled version of the IV coefficients so we do not evaluate their economic magnitude. In columns (2) - (3) we focus on *Intra-firm mobility* and *Inter-firm mobility*, and continue to find lower mobility among individuals with higher *SLTV* even in our most stringent specification.

One concern with our results is the extent to which they are dependent on the specific LTV or SLTV buckets we pick. To evaluate the importance of this concern in Figure 5, we repeat the reduced form estimation with dummies to indicate 17 different SLTV buckets instead of the five we had in Table 3. We construct these buckets as follows. We divide the SLTV values in our sample (that range from zero to two) into 20 different buckets of 0.1 width each. Since, the number of observations with SLTV greater than 1.7 are very small, we combine the last four buckets into one - $SLTV \in (1.7, 2]$. As before, the omitted category is the bucket with $SLTV \in (0.7, 0.8]$. Figure 5 illustrates results for this reduced form regression with both within ZIPcode time effects and within purchase cohort time effects.

In Panel (a) of Figure 5 we model *Mobility* and present the coefficient estimates and confidence intervals (CI) at 95% level. The estimates suggest that mobility of individuals with SLTV less than 0.7 is not statistically different from that for individuals with $SLTV \in (0.7, 0.8]$. We find that the coefficients progressively go down with SLTV. Interestingly we do find a slight uptick in mobility for individuals with extremely high SLTV values (i.e. $SLTV > 1.6$). A possible reason for the uptick in labor mobility at very high *SLTV* values could be due to individuals defaulting on their mortgage when it is significantly underwater. We explore this in our tests that distinguish between delinquence and mobility not associated with a delinquency.

In Panels (b) and (c), we study *Intra-firm* and *Inter-firm* mobility and continue to find a monotonic relationship between SLTV and labor mobility. Higher SLTVs are associated with lower mobility.

In Table 4 we present the results of the IV regression described in equation (5). As mentioned before, for each IV estimation, we have four first stage regressions one for each LTV bucket indicator. We use the corresponding SLTV bucket indicator as the instrument for the LTV bucket indicator. In the first panel of Table 4 we provide the coefficients along with F-statistic for each of the first stage regressions. We report these results for the specification which includes both within ZIPcode and within purchase cohort time effects. From the reported results, we find that all the instruments are strong and the F-statistics are significantly larger than the threshold of 10

(Bound et al. [1995], Staiger and Stock [1997]).

Panel B reports the coefficients for the second stage. The results in column (1) show that consistent with our OLS results, labor mobility decreases with home LTV. Comparing the magnitude of our coefficient estimates between the OLS and IV specifications, we find that our point estimates are almost identical. For example our IV estimate indicates that individuals with $LTV \in [1, 1.4)$ and those with $LTV \in [> 1.4]$ have 0.3% lower mobility as compared to individuals with $LTV \in [0.7, 0.8)$. Our OLS estimates are also similar. Thus the endogeneity of loan amounts does not appear to have a significant effect on our coefficient estimates. As before, these results are economically very large when compared to the sample mean mobility of 0.6%.

In column (2) we focus on intra-firm mobility. Here again our results strongly indicate lower mobility among individuals with higher LTVs and our IV estimates are similar to our OLS estimates. Finally in column (3) we focus on inter-firm mobility and again find that individuals with higher LTVs have lower mobility than individuals with $LTV \in [0.7, 0.8)$. Interestingly our IV estimates in column (3) are larger than the OLS estimates. For example from column (3) we find that individuals with $LTV \in [1, 1.4)$ and those with $LTV \in [> 1.4]$ have 0.1% lower mobility as compared to individuals with $LTV \in [0.7, 0.8)$. In contrast our OLS estimates indicate that these two groups of individuals have .05% and .04% lower mobility respectively with the latter not being statistically significant. Thus when it comes to inter-firm mobility we find that the endogenity of loan amounts biases our OLS estimates downward.

5.2 Home Equity, Delinquency & Labor Mobility

In this section, we investigate the effect of LTV on mortgage delinquency and consequent mobility. The dependent variable in column (1) of Table 5 is *Delinquency* and in the specification we include within ZIPcode time effects and exclude within cohort time effects. The results indicate a monotonic increase in the default probability with LTV. Individuals with mortgages with higher LTV are more likely to become delinquent. In column (2) we repeat our tests after including within cohort time effects. Here again we find a monotonic increase in the probability of *Delinquency* with LTV. The results indicate that individuals with $LTV \in [1, 1.4)$ and $LTV \in [> 1.4]$ are both 0.1% more likely to default on their mortgage as compared to individuals with $LTV \in [0.7, 0.8)$. These results are economically large when compared to the mean value of *Delinquency* of 0.2% in our sample. Interestingly there does not appear to be a cohort effect when it comes to mortgage delinquency. This is evident from the fact that the coefficients in column (2) – where we control for cohort effects – are of similar magnitude as those in column (1).

Note that delinquent borrowers will need to move from their residence eventually. In our analysis of mobility in Tables 2-4, we do not differentiate between mobility that is accompanied by delinquency and mobility that is not. In columns (3) - (4) we focus on mobility not associated with mortgage delinquency. Thus our dependent variable in this specification turns on when there is a change in the ZIPcode of an individual in month *t+1* and the individual is current on her mortgage in month *t*. Here again, not surprisingly we find a strong negative association between LTV and mobility. We also find our results to be economically large. For example the coefficients on $LTV \in [1, 1.4)$ and $LTV \in [> 1.4]$ are 0.3% and 0.4% respectively in column (4) of Table 5. In comparison when we look at mobility without distinguishing those associated with mortgage delinquency, we find the coefficients on $LTV \in [1, 1.4)$ and $LTV \in [1.4, 2]$ to be 0.3% each (see column (2) of Table 2). As before, the economic magnitudes of these results are very large when compared to the mean value for non-delinquent mobility of 0.4% in our sample.

In Figure 6, we implement a reduced form specification wherein we include dummies to indicate 17 SLTV buckets. We construct these buckets in the same manner as in Figure 5. We implement the model including both within ZIPcode time effects and within purchase cohort time effects. In Panel (a) we model *Delinquency* and present the coefficient estimates and the 5% and 95% confidence intervals (CI). The estimates suggest a monotonic relationship between *Delinquency* and SLTV. Our CIs are large for the high SLTV buckets because of fewer observations. In Panel B we focus on mobility not associated with a delinquency and find that unlike in Figure 6, wherein we focus on aggregate mobility, we no longer find an uptick in mobility in the high

SLTV buckets. This confirms our conjecture that the increase in mobility at higher SLTVs are a result of mortgage defaults.

In Table 6 we present the results of the IV regression described in equation (5) with delinquency and non-delinquent mobility as the dependent variables. The results in column (1) show that consistent with our OLS results, delinquency increases with home LTV. Comparing the magnitude of our coefficient estimates between the OLS and IV specifications, we find that our point estimates are smaller with the IV specification as compared to the OLS specification. For example our IV estimate indicates that individuals with $LTV \in [> 1.4]$ have 0.02% higher probability of default as compared to individuals with $LTV \in [0.7, 0.8)$. In comparison our OLS estimates indicate (see column (2) of Table 5) that individuals with $LTV \in [> 1.4]$ have a 0.1% higher probability of default. In column (2) we focus on mobility not associated with delinquency. Again we find that individuals with higher LTVs are less likely to move than individuals with $LTV \in [0.7, 0.8)$. The coefficients for the IV estimation are similar in magnitude to our OLS estimates.

A potential concern with our analysis is that our sample may not be representative of the population of mortgage borrowers in the U.S. since the employment data is not comprehensive. To alleviate these concerns, we repeat our baseline analysis with a random sample of individuals from the more comprehensive credit data. In Table 7 we report coefficients for IV regressions that estimate the effect of LTV on different forms of mobility for this more representative sample. In column (1) we report estimates for *Mobility* where we find results similar to our main sample, i.e. individuals with higher LTV on average have lower mobility. Specifically, we find that compared to individuals with $LTV \in (0.7, 0.8]$, those with $LTV \in (0.8, 1]$ and $LTV \in (1, 1.4]$ are both 0.1% less likely to move. In columns (2) and (3), we report results for *Delinquency* and *Non-Delinquent Mobility.* Similar to our estimates with the main sample, we find that individuals with $LTV \in (1, 1.4]$ have 0.1% higher probability of *Delinquency* and 0.5% lower probability of *Non-Delinquent Mobility* compared to individuals with $LTV \in (0.7, 0.8]$.

Overall, these results suggest that while some individuals with high LTV default and subsequently move, the group of individuals that don't default are less likely to move as LTV goes up.

5.3 Heterogeneous Effects : Access to Credit & Liquidity

In this section, we differentiate individuals based on their access to credit and tenure in the firm to see if there is any difference in the effect of LTV on labor mobility.

In Panel A of Table 8 we differentiate between *Prime* and *Subprime* borrowers and estimate the effect of home LTV on labor mobility. We expect subprime borrowers to face greater credit constraints as compared to prime borrowers. If LTV affects labor mobility because of credit constraints then we expect this effect to be stronger for the subprime borrowers. In these tests, we employ the reduced form model with both within ZIPcode time effects and within cohort time effects. Thus the identification comes from differences in mobility between individuals from the same ZIPcode belonging to different cohorts after netting out average cohort effects. We perform our cross-sectional tests by including interaction terms between the indicator variables that identify SLTV buckets and *Prime* and *Subprime*, dummy variables that identify prime and subprime borrowers respectively. Based on industry practice, we classify individuals with credit score above 620 as of Jan 2010 as *Prime* and those with credit score below 620 as of that date as *Subprime*.

The outcome variable in column (1) is *Mobility*. Although we include interaction terms with the full set of SLTV indicator variables, to conserve space we only report the coefficients on the interaction terms with $1_{\{1 \leq SLTV_{it} < 1.4\}}$ and $1_{\{SLTV_{it} \geq 1.4\}}$. We find that the effect of SLTV on labor mobility is greater for subprime borrowers as compared to for prime borrowers. We find that the coefficients on the interaction terms involving *Subprime* are statistically different from those involving *Prime*. In column (2) we model *Delinquency* and again find that *Subprime* borrowers are more likely to become delinquent at high SLTVs as compared to *Prime* borrowers. Finally in column (3) we focus on mobility not involving a mortgage delinquencyand and again find that SLTV has a larger effect on the mobility of subprime borrowers as compared to prime borrowers.

In Panel B of Table 8 we differentiate borrowers based on their access to liquidity. We measure borrower access to liquidity based on the aggregate amount of undrawn credit limits in their card accounts. We classify borrowers with above (below) median undrawn limits as a proportion of mortgage outstanding as of Jan 2010 as having *Above* (*Below*) median access to liquidity. Here again we expect SLTV to especially affect the mobility of borrowers with less access to liquidity. From column (1) we find that while higher SLTV lowers mobility for borrowers *with Below* median access to liquidity, it does not affect the mobility of borrowers with *Above* median access to liquidity. In column (2) we model *Delinquency* and again find that borrowers with less liquidity are more likely to become delinquent at high SLTVs as compared to borrowers with more liquidity. Finally in column (3) we focus on mobility not involving a mortgage delinquencyand again find that the mobility of borrowers with less liquidity are affected to a greater extent by higher SLTV.

To summarize, the results in this section show that SLTV has an incrementally stronger effect on the mobility of sub-prime borrowers and individuals with below median access to liquidity.

5.4 Home Equity, Income and Promotion

The results presented so far show that individuals with high home LTV are less likely to move suggesting that such individuals may be foregoing some attractive job opportunities. In this section we test to see if this hinders their career progression leading to lower income and lower likelihood of promotion. We present the results in Table 9. In these tests, we employ the IV regressions with both within ZIPcode time effects and within cohort time effects. Although we include the full set of LTV indicator variables, to conserve space we only report the coefficients on indicator functions $1_{\{1 \leq LTV_{it} < 1.4\}}$ and $1_{\{LTV_{it} \geq 1.4\}}$. In column (1) our dependent variable is the logarithm of monthly income and we find that individuals with LTV values greater than 0.8 have lower income than individuals with $LTV \in [0.7, 0.8)$. Our estimates indicate that income for individuals with $LTV \in [1, 1.4)$ is 0.4% lower than that for individuals with $LTV \in [0.7, 0.8)$.

In column (4) we focus on job promotions. We define job promotions as instances where monthly income increases by more than 10%. We create an indicator variable, *Job Promotion* that turns on during month t if the monthly income increases by more than 10% in month $t+1$. In column (4) we find that individuals with $LTV \in [1, 1.4)$ are less likely to be promoted than individuals with $LTV \in [0.7, 0.8)$. Our two-stage IV estimates indicate that individuals with $LTV \in [1, 1.4)$ are 0.3% less likely to be promoted than individuals with $LTV \in [0.7, 0.8)$. We find that our results are robust to defining job promotions as instances when income increases by 15% or 20%.

A negative association between LTV and income is also consistent with the labor supply channel outlined in Bernstein [2016]. Individuals with very high LTV may have lower incentives to improve their labor income as a larger fraction of the income gain may go towards debt service. To differentiate the Credit constraint channel from the labor-supply channel, we differentiate individuals based on access to liquidity. In these tests we also control for the aggregate amount of liabilities. The negative effect of leverage on labor supply should not vary with an individual's access to liquidity. On the other hand to the extent accress to liquidity relaxes credit constraints, we expect the negative association between LTV and labor income to be weaker for individuals with greater access to liquidity.

We test this in columns (2) and (5) of Table 9 by classifying borrowers with above (below) median undrawn limits as a proportion of mortgage outstanding as of Jan 2010 as having *Above* (*Below*) median access to liquidity. As before, we include interaction terms between the indicator variables that identify LTV buckets and *Above* and *Below*. In column (2) we find that while higher LTV lowers income for borrowers *Below* median access to liquidity, it does not affect income for borrowers with *Above* median access to liquidity. The coefficients in column (2) suggest that income for individuals with $LTV \in [1, 1.4)$ having *Below* median access to liquidity is 2% lower than individuals with $SLTV \in [0.7, 0.8)$. In column (5) we focus on *Job Promotion* and find that high LTV lowers the likelihood of promotion for individuals with *Below* median access to liquidity but has no effect for individuals with *Above* median access to liquidity.

In columns (3) and (6) we differentiate individuals based on tenure in their job. We expect the constraints on mobility to affect income for individuals who have been in the current job for a longer period of time. When the individual is new to a job her ability to move may impose lower constraints on her income growth. On the other hand once an individual has spent significant time in a job, not only will mobility be important in her growth in the organization, but mobility may also be essential to take up a higher paying jobs. Thus, we expect LTV to especially affect the income and promotion of individuals with greater tenure. In columns columns (3) and (6) we differentiate individuals into those with less (more) than two years tenure in the current job and we find that LTV lowers income and likelihood of promotion for individuals with tenure greater than two years but does not affect individuals with tenure less than two years. Overall, these results are consistent with lower mobility affecting income and job promotion.

5.5 Home Equity & Job Mobility not involving Geographic Mobility

In this section, we investigate if individuals with high LTV are more likely to move jobs without moving residence. To the extent such individuals face constraints on geographic mobility, they may be more inclined to look for attractive job opportunities closer to their current residence. To test this conjecture we construct an indicator variable, *Within-ZIPcode mobility* that captures job mobility in the absence of geographic mobility. It turns on in month t if the individual changes employer while residing in the same ZIPcode in month $t+1$.

In Table 10 we report results for the effect of SLTV on job mobility not involving geographic mobility. In column (1) we present the OLS estimates after including within ZIPcode and within cohort time effects. We find that individuals with LTV greater than one are more likely to move jobs without moving residence. Our results are economically significant. Our results indicate that individuals with LTV greater than 1 are 0.2% more likely to move jobs without moving residence as compared to individuals with $LTV \in [0.7, 0.8)$. In comparison the average probability of an individual moving jobs without moving residence in our sample is 1.6%. In column (2) we present the second stage of our IV estimate and find our results to be similar to our OLS estimates.

6 Robustness

6.1 Measurement Error Problem

A potential concern with our analysis is that the main independent variable may be subject to measurement error because we don't observe the purchase value of the house and make an assumption on the value of LTV at origination. To ensure that our results are not driven by this assumption, we repeat our analysis with different values of LTV at origination. Panel A of Table 11 reports results for this estimation. In, Columns (1) through (3) we allow values for LTV at origination to vary between 0.70 and 0.80 with increments of 0.05 and find similar results as our baseline estimates (Column (1)). Individuals with $LTV \in [1.0, 1.4)$ are 0.2-0.4 percentage points less likely to move in any given month than individuals with $LTV \in [0.7, 0.8)$. Column (4) assumes the value of LTV at origination as 0.80 for individuals who originate only one primary mortgage, and 0.90 for individuals who originate a secondary mortgage along with a primary mortgage at the time of home purchase. The estimates in column (4) show that individuals with $LTV \in [1.0, 1.4)$ are 0.3 percentage points less likely to move in any given month than individuals with $LTV \in [0.7, 0.8)$.

Another similar concern may be that our IV and reduced form estimates may be sensitive to our choice of interest rate for constructing the instrument. To mitigate this concern, we repeat our estimation assuming different values of interest rates for constructing our instrument. Panel B of Table 11 reports coefficients for this estimation. We allow interest rates to vary between 5.75% and 7.75% with the increments of 0.50% and find results similar to our baseline estimates (Column (3)). Individuals with $LTV \in [1.0, 1.4)$ are 0.1-0.3 percentage points less likely to move in any given month than individuals with $LTV \in [0.7, 0.8)$.

6.2 Definition of Mobility

In our baseline specification, we define mobility as change in the ZIPcode of an individual's primary residence. This definition may not capture labor mobility if individuals move houses within the same region while continuing to be employed at the same establishment within the same firm. This can be particularly problematic for our results on *Intra-firm mobility.*

To ensure that our results are not driven by this mis-specification of labor mobility, we define mobility as changes in MSA and state of an individual's primary residence, and repeat our analysis. Table 12 reports estimates for this analysis. Columns (1) through (3) report results where mobility is defined at the MSA level while columns (4) through (6) defines mobility at the state level. Consistent with our baseline specification, we find that individuals with $LTV \in [1.0, 1.4)$ are less likely to move (unconditionally, within and across firms) in any given month than individuals with $LTV \in [0.7, 0.8)$.

7 Conclusion

The great recession has heightened interest in understanding how house prices and mortgage debt affect individual consumption and investment behavior. We use detailed credit profile and employment data of a large sample of individuals to estimate the effect of mortgage debt on labor mobility. Mortgage debt – when extreme – can affect labor mobility if an individual is credit constrained and if there are some (perceived) costs of renting a house (Stein [1995], Ortalo-Magne and Rady [2006]). If a house is underwater, a home owner facing the prospect of moving has to compensate the bank for the shortfall between the sale price and mortgage outstanding. Her ability to do this will depend on the availability of liquidity and the extent to which she is credit constrained.

We focus on homeowners as of January 1, 2010, follow their employment trajectory till they move residence or cease employment to understand the effect of mortgage debt on labor mobility. We measure the amount of mortgage debt by the loan to value ratio (LTV) on the primary residence. We aggregate the outstanding balance on both the primary morgage and home equity lines of credit to measure loan outstanding and use house price index at the ZIPcode level obtained from Corelogic to capture house price changes.

In our OLS and IV specification, we find a strong negative relationship between LTV and mobility defined as an individual moving from one ZIPcode to another. We find that this is robust to including individual, within ZIPcode time and within purchase cohort time fixed effects. As compared to individuals with *LTV* between 0.7 and 0.8, individuals with LTV between 1 and 1.4 are 0.3% less likely to move in a month. In comparison, the mean mobility of the individuals in our sample is 0.6% per month. We find that the negative effect of LTV on labor mobility is stronger for sub-prime borrowers and for those with below median undrawn credit limit relative to the mortgage outstanding.

While the probability of mortgage delinquency does increase with LTV, overall LTV has a negative effect on mobility. We further find that LTV depresses labor income and job promotion especially for individual that have less access to liquidity and that have spent more than two years in the current job. Finally we find that individuals with high LTVs have higher intra-ZIPcode job mobility.

The spillover effects from the housing market to the labor market that we document should be considered by policy makers when faced with future house price declines. Our results may also go towards explaining the slow recovery in employment following the house price decline during the great recession. Our results also have relevance for companies interested in retaining and developing human talent. Our results show that employee credit constraints may be an important factor that affects their willingness to move to take up new challenges. Our results call for more proactive policies on the part of companies to help such employees relocate.

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Table 1: Summary Statistics

This table reports the sample statistics of the variables used in this analysis. These are reported by subgroups of dependent and independent variables respectively.

	N	Mean	St. Dev.	Min	Median	Max
Labor Mobility & Income						
Mobility	13,389,609	0.006	0.1	0	0	1
Intra-Firm mobility	13,389,609	0.004	0.1	0	0	1
Inter-Firm mobility	13,389,609	0.002	0.04	0	0	1
Delinquencies	13,389,609	0.002	0.01	0	0	1
Non-Delinquent mobility	13,389,609	0.004	0.1	0	0	1
Monthly income ('000s $)	13,389,609	6.728	9.820	0.400	5.272	391.807
Within-ZIPcode mobility	13,389,609	0.016	0.13	0	0	1
LTV & Distribution						
Original loan amount ('000s $)	13,389,609	170.376	120.140	717	140.000	3,451.099
Purchase price ('000s $)	13,389,609	243.395	171.627	1.024	200.000	4,930.141
Loan balance ('000s $)	13,389,609	130.832	120.411	0	104.967	3,451.099
Home value ('000s $)	13,389,609	250.931	171.171	0.739	207.626	7,778.388
LTV	13,389,609	0.5	0.3	0	0.6	2
SLTV	13,389,609	0.7	0.2	0	0.7	1.9
$\mathbf{1}_{\{LTV=0\}}$	13,389,609	0.15	0.4	0	0	1
$\mathbf{1}_{\{0<LTV<0.7\}}$	13,389,609	0.6	0.5	0	1	1
$\mathbf{1}_{\{0.7\leq LTV<0.8\}}$	13,389,609	0.1	0.	0	0	1
$\mathbf{1}_{\{0.8\leq LTV<1\}}$	13,389,609	0.1	0.3	0	0	1
$\mathbf{1}_{\{1\leq LTV<1.4\}}$	13,389,609	0.04	0.2	0	0	1
$\mathbf{1}_{\{1.4\leq LTV\}}$	13,389,609	0.01	0.1	0	0	1
$\mathbf{1}_{\{SLTV=0\}}$	13,389,609	0.0	0.004	0	0	1
$\mathbf{1}_{\{0<SLTV<0.7\}}$	13,389,609	0.6	0.5	0	1	1
$\mathbf{1}_{\{0.7\leq SLTV<0.8\}}$	13,389,609	0.1	0.	0	0	1
$\mathbf{1}_{\{0.8\leq SLTV<1\}}$	13,389,609	0.2	0.4	0	0	1
$\mathbf{1}_{\{1\leq SLTV<1.4\}}$	13,389,609	0.1	0.2	0	0	1
$\mathbf{1}_{\{1.4\leq SLTV\}}$	13,389,609	0.01	0.1	0	0	1

Table 2: Home Equity & Labor Mobility : OLS

This table reports the coefficient estimates from the following OLS regressions that estimate the effect of LTV on labor mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq LTV_{it} < h_k\}} + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode× month fixed effects, δ_{ct} are purchase cohort×month fixed effects, the indicator functions, $1_{\{l_k \leq LTV_{it} \leq h_k\}}$ indicate different LTV value buckets which turn on when the loan-to-value ratio (LTV) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $LTV_{it} \in (l_k, h_k)$, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket $(0.7.0.8]$ as base for comparison. The dependent variable y_{iczt} represents different measures of mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

	Mobility		Intra-firm mobility		Inter-firm mobility	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}_{\{0<LTV<0.7\}}$	0.001***	0.001**	0.001***	0.0002	0.001***	0.0003***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$\mathbf{1}_{\{0.8 \leq LTV<1\}}$	-0.003***	0.0004*	-0.003***	-0.0001	-0.001***	0.0003***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$\mathbf{1}_{\{1 \leq LTV<1.4\}}$	-0.005***	-0.003***	-0.005***	-0.001***	-0.001***	-0.0005**
	(0.0005)	(0.001)	(0.0003	(0.0004)	(0.0002)	(0.0002)
$\mathbf{1}_{\{1.4 \leq LTV\}}$	-0.009***	-0.003***	-0.008***	-0.004***	-0.002***	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.0004)
Tenure Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIPcode×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Purchase cohort×Month FE	No	Yes	No	Yes	No	Yes
Observations	13,389,609	13,389,609	13,389,609	13,389,609	13,389,609	13,389,609
R^2	0.205	0.209	0.186	0.188	0.095	0.096

Table 3: Home Equity & Labor Mobility : Reduced Form

This table reports the coefficient estimates from the following reduced form regressions that estimate the effect of SLTV on labor mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq SLTV_{it} \leq h_k\}}$ indicate different SLTV value buckets which turn on when the synthetic loan-to-value ratio ($SLTV$) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $SLTV_{it} \in (l_k, h_k)$, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents different measures of mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

	Mobility (1)	Intra-firm mobility (2)	Inter-firm mobility (3)
$\mathbf{1}_{\{0<SLTV<0.7\}}$	0.0004**	0.0002*	0.0002**
	(0.0002)	(0.0001)	(0.0001)
$\mathbf{1}_{\{0.8 \leq SLTV<1\}}$	0.0003*	0.00001	-0.0002***
	(0.0002)	(0.0001)	(0.0001)
$\mathbf{1}_{\{1 \leq SLTV<1.4\}}$	-0.001***	-0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0002)
$\mathbf{1}_{\{1.4 \leq SLTV\}}$	-0.002**	-0.002***	-0.001***
	(0.001)	(0.001)	(0.0004)
Tenure Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609
R^2	0.172	0.182	0.127

Table 4: Home Equity & Labor Mobility : IV Regression

This table reports the coefficient estimates from the following IV regressions that estimate the effect of LTV on labor mobility:

$$1_{\{l_k \le LTV_{it} < h_k\}} = \delta_i + \delta_{zt} + \delta_{ct} + 1_{\{l_k \le SLTV_{it} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k 1_{\{l_k \widehat{\le LTV_{it}} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \le LTV_{it} \le h_k\}}$ ($1_{\{l_k \le SLTV_{it} \le h_k\}}$) indicate different LTV (SLTV) value buckets which turn on when the loan-to-value (synthetic loan-to-value) ratio of an individual's primary residence at the end of month t is between l_k and h_k, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents different measures of mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

Panel A: First stage regression				
	$\mathbf{1}_{\{0<LTV<0.7\}}$	$\mathbf{1}_{\{0.8 \le LTV<1\}}$	$\mathbf{1}_{\{1 \le LTV<1.4\}}$	$\mathbf{1}_{\{1.4 \le LTV\}}$
	(1)	(3)	(4)	(5)
$\mathbf{1}_{\{0<SLTV<0.7\}}$	0.562***	-0.027***	0.001**	0.002***
	(0.006)	(0.002)	(0.0004)	(0.0002)
$\mathbf{1}_{\{0.8 \le SLTV<1\}}$	-0.116***	0.529***	0.022***	-0.004***
	(0.004)	(0.006)	(0.001)	(0.0004)
$\mathbf{1}_{\{1 \le SLTV<1.4\}}$	-0.180***	0.100***	0.563***	0.006***
	(0.007)	(0.004)	(0.007)	(0.001)
$\mathbf{1}_{\{1.4 \le SLTV\}}$	-0.187***	0.060***	0.178***	0.482***
	(0.01)	(0.006)	(0.008)	(0.012)
Tenure Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
ZIPcode×Month FE	Yes	Yes	Yes	Yes
Purchase cohort×Month FE	Yes	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609	13,389,609
F-Statistic	67.52	35.86	45.44	39.14

Table 4 (contd)

Panel B: Second stage regression			
	Mobility (1)	Intra-firm mobility (2)	Inter-firm mobility (3)
$\mathbf{1}_{\{0<\widehat{LTV}<0.7\}}$	0.001***	0.0004**	0.0003**
	(0.0003)	(0.0002)	(0.0002)
$\mathbf{1}_{\{\widehat{\mathbf{0.8\leq LTV}}<\mathbf{1}\}}$	0.0004	0.00002	0.0004***
	(0.0003)	(0.0002)	(0.0001)
$\mathbf{1}_{\{\widehat{\mathbf{1.0\leq LTV}}<\mathbf{1.4}\}}$	-0.003***	-0.002**	-0.001***
	(0.001)	(0.001)	(0.0005)
$\mathbf{1}_{\{\widehat{\mathbf{1.4\leq LTV}}\}}$	-0.003**	-0.003***	-0.001***
	(0.001)	(0.001)	(0.001)
Tenure Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
ZIPcode×Month FE	Yes	Yes	Yes
Purchase cohort×Month FE	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609
R^2	0.172	0.182	0.128

Table 5: Home Equity, Delinquency & Mobility : OLS

This table reports the coefficient estimates from the following OLS regressions that estimate the effect of LTV on delinquency and non-delinquent mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq LTV_{it} < h_k\}} + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq LTV_{it} \leq h_k\}}$ indicate different LTV value buckets which turn on when the loan-to-value ratio (LTV) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $LTV_{it} \in (l_k, h_k)$, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket $(0.7.0.8]$ as base for comparison. The dependent variable y_{iczt} represents measures of delinquency and non-delinquent mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

	Delinquency		Non-delinquent mobility	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{0<LTV<0.7\}}$	-0.0001***	-0.00005***	0.001***	0.001***
	(0.00003)	(0.00001)	(0.0003)	(0.0002)
$\mathbf{1}_{\{0.8\leq LTV<1\}}$	0.0002	0.0002	-0.002***	-0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$\mathbf{1}_{\{1\leq LTV<1.4\}}$	0.001**	0.001**	-0.006***	-0.003***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
$\mathbf{1}_{\{1.4\leq LTV\}}$	0.001**	0.001**	-0.010**	-0.004***
	(0.0004)	(0.0005)	(0.0005)	(0.001)
Tenure Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes	Yes	Yes
Purchase cohort$\times$Month FE	No	Yes	No	Yes
Observations	13,389,609	13,389,609	13,389,609	13,389,609
R^2	0.117	0.117	0.159	0.164

Table 6: Home Equity, Delinquency & Mobility: IV Regression

This table reports the coefficient estimates from the following IV regressions that estimate the effect of LTV on delinquency and non-delinquent mobility:

$$1_{\{l_k \leq LTV_{it} \leq h_k\}} = \delta_i + \delta_{zt} + \delta_{ct} + 1_{\{l_k \leq SLTV_{it} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k 1_{\{\widehat{l_k \leq LTV_{it}} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq LTV_{it} \leq h_k\}}$ ($1_{\{l_k \leq SLTV_{it} \leq h_k\}}$) indicate different LTV (SLTV) value buckets which turn on when the loan-to-value (synthetic loan-to-value) ratio of an individual's primary residence at the end of month t is between l_k and h_k, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket $(0.7.0.8]$ as base for comparison. The dependent variable y_{iczt} represents measures of delinquency and non-delinquent mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Delinquency	Non-delinquent mobility
	(1)	(2)
$\mathbf{1}_{\{\widehat{0<LTV<0.7}\}}$	0.0001	-0.0001
	(0.0001)	(0.0003)
$\mathbf{1}_{\{\widehat{0.8\leq LTV<1}\}}$	0.00003	0.001**
	(0.00004)	(0.0003)
$\mathbf{1}_{\{\widehat{1.0\leq LTV<1.4}\}}$	0.001***	-0.004***
	(0.0004)	(0.001)
$\mathbf{1}_{\{\widehat{1.4\leq LTV}\}}$	0.0002**	-0.003***
	(0.0001)	(0.001)
Tenure Controls	Yes	Yes
Individual FE	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes
Observations	13,389,609	13,389,609
R^2	0.117	0.163

Table 7: Home Equity, Delinquency & Mobility: Credit Data Sample

This table reports the coefficient estimates from the following IV regressions that estimate the effect of LTV on mobility, delinquency and non-delinquent mobility for the credit data sample:

$$1_{\{l_k \le LTV_{it} \le h_k\}} = \delta_i + \delta_{zt} + \delta_{ct} + 1_{\{l_k \le SLTV_{it} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k 1_{\{l_k \le \widehat{LTV_{it}} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \le LTV_{it} \le h_k\}}$ ($1_{\{l_k \le SLTV_{it} \le h_k\}}$) indicate different LTV (SLTV) value buckets which turn on when the loan-to-value (synthetic loan-to-value) ratio of an individual's primary residence at the end of month t is between l_k and h_k, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket $(0.7.0.8]$ as base for comparison. The dependent variable y_{iczt} represents measures of delinquency and non-delinquent mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Mobility (1)	Delinquency (2)	Non-delinquent mobility (3)
$\mathbf{1}_{\{0<\widehat{LTV}<0.7\}}$	0.0000	0.0001	0.001
	(0.0004)	(0.0001)	(0.0004)
$\mathbf{1}_{\{\mathbf{0.8}\le\widehat{\mathbf{LTV}}<\mathbf{1}\}}$	-0.001***	0.0002*	-0.001***
	(0.0004)	(0.0001)	(0.0004)
$\mathbf{1}_{\{\mathbf{1.0}\le\widehat{\mathbf{LTV}}<\mathbf{1.4}\}}$	-0.001***	0.001**	-0.005***
	(0.0004)	(0.0004)	(0.001)
$\mathbf{1}_{\{\mathbf{1.4}\le\widehat{\mathbf{LTV}}\}}$	-0.002	0.00001	-0.003*
	(0.003)	(0.0003)	(0.002)
Tenure Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes	Yes
Observations	13,768,613	13,768,613	13,768,613
R^2	0.197	0.134	0.19

Table 8: Heterogeneous Effects: Reduced Form Regression

This table reports the coefficient estimates from the following reduced form regressions that estimate the heterogeneous effects of LTV on mobility, delinquency and non-delinquent mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} \times Above + \sum_k \alpha_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} \times Below + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq SLTV_{it} \leq h_k\}}$ indicate different SLTV value buckets which turn on when the synthetic loan-to-value ratio ($SLTV$) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $SLTV_{it} \in (l_k, h_k)$, $Above$ ($Below$) is a dummy variable that takes a value of 1 for individuals with above (below) median values for the cross-sectional variable and X_{it} are quadratic controls for individual's tenure at the firm. We exclude SLTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents different measures of mobility, delinquency and non-delinquent mobility. For brevity, we only present results for SLTV buckets with values greater than one. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

Panel A: Prime vs subprime borrowers			
	Mobility	Delinquency	Non-delinquent Mobility
	(1)	(2)	(3)
$\mathbf{1}_{\{1 \leq SLTV < 1.4\}} \times Prime$	-0.001***	0.0001**	-0.001**
	(0.0004)	(0.00005)	(0.0004)
$\mathbf{1}_{\{1 \leq SLTV < 1.4\}} \times Subprime$	-0.005***	0.0004***	-0.002***
	(0.001)	(0.00004)	(0.0005)
$\mathbf{1}_{\{1.4 \leq SLTV\}} \times Prime$	0.001	0.0003***	-0.001**
	(0.001)	(0.0001)	(0.001)
$\mathbf{1}_{\{1.4 \leq SLTV\}} \times Subprime$	-0.007***	0.0003***	-0.004***
	(0.002)	(0.0001)	(0.001)
$\mathbf{1}_{\{1 \leq SLTV < 1.4\}}$[Prime-Subprime]	0.004***	-0.0003***	0.001*
$\mathbf{1}_{\{1.4 \leq SLTV\}}$[Prime-Subprime]	0.008***	0.000	0.003**
Tenure Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609
R^2	0.172	0.117	0.163

Table 8 (contd)

Panel B: High vs Low Access to Liquidity			
	Mobility	Delinquency	Non-delinquent Mobility
	(1)	(2)	(3)
$\mathbf{1}_{\{1 \leq SLTV < 1.4\}} \times Above$	0.001	-0.001**	0.0004
	(0.001)	(0.0003)	(0.0004)
$\mathbf{1}_{\{1 \leq SLTV < 1.4\}} \times Below$	-0.002***	0.001***	-0.002***
	(0.0004)	(0.0003)	(0.0004)
$\mathbf{1}_{\{1.4 \leq SLTV\}} \times Above$	0.001	-0.001*	0.002**
	(0.001)	(0.0005)	(0.001)
$\mathbf{1}_{\{1.4 \leq SLTV\}} \times Below$	-0.005***	0.001***	-0.002***
	(0.001)	(0.0002)	(0.001)
$\mathbf{1}_{\{1 \leq SLTV < 1.4\}}$[Above-Below]	0.003***	-0.002***	-0.002***
$\mathbf{1}_{\{1.4 \leq SLTV\}}$[Above-Below]	0.006***	-0.001***	-0.004***
Tenure Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
ZIPcode×Month FE	Yes	Yes	Yes
Purchase cohort×Month FE	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609
R^2	0.108	0.034	0.108

Table 9: Home Equity, Restricted Mobility & Income

This table reports the coefficient estimates from the following reduced form regressions that estimate the effect of LTV on income and job promotions:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} \times Above + \sum_k \alpha_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} \times Below + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq SLTV_{it} \leq h_k\}}$ indicate different SLTV value buckets which turn on when the synthetic loan-to-value ratio ($SLTV$) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $SLTV_{it} \in (l_k, h_k)$, *Above* (*Below*) is a dummy variable that takes a value of 1 for individuals with above (below) median values of access to liquidity when the cross-sectional variable is access to liquidity while taking a value of 1 for individuals with tenure greater than 2 years when the cross-sectional variable is tenure, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude SLTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents income and job promotions. For brevity, we only present results for SLTV buckets with values greater than one. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

	Log(Income)			Job Promotion		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}_{\{\widehat{\mathbf{1.0 \leq LTV < 1.4}}\}}$	-0.004***			-0.003**		
	(0.001)			(0.001)		
$\mathbf{1}_{\{\widehat{\mathbf{1.4 \leq LTV}}\}}$	-0.001			0.0004		
	(0.011)			(0.001)		
$1_{\{\widehat{1.0 \leq LTV < 1.4}\}} \times Above$		0.001	-0.130***		-0.0001	-0.003**
		(0.01)	(0.042)		(0.001)	(0.001)
$1_{\{\widehat{1.0 \leq LTV < 1.4}\}} \times Below$		-0.02**	0.009		-0.003***	0.002
		(0.004)	(0.011)		(0.001)	(0.004)
$\mathbf{1}_{\{\widehat{\mathbf{1.4 \leq LTV}}\}} \times Above$		0.064	-0.0002		0.007	0.0002
		(0.084)	(0.011)		(0.012)	(0.001)
$\mathbf{1}_{\{\widehat{\mathbf{1.4 \leq LTV}}\}} \times Below$		-0.002	0.005		0.0001	0.006
		(0.009)	(0.049)		(0.001)	(0.005)
Cross Sectional Variable		Liquidity	Tenure		Liquidity	Tenure
$1_{\{\widehat{1.0 \leq LTV < 1.4}\}}$[Above-Below]		0.021**	-0.139***		0.003**	-0.005
$\mathbf{1}_{\{\widehat{\mathbf{1.4 \leq LTV}}\}}$[Above-Below]		0.066	-0.005		0.007	-0.006
Tenure Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,952,187	10,952,187	10,952,187	13,389,609	13,389,609	13,389,609
R^2	0.946	0.946	0.946	0.12	0.12	0.12

Table 10: Home Equity & Within-ZIPcode Mobility

This table reports the coefficient estimates from the following reduced form regressions that estimate the effect of SLTV on job mobility that does not involve geographic mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq SLTV_{it} < h_k\}} + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq SLTV_{it} \leq h_k\}}$ indicate different SLTV value buckets which turn on when the synthetic loan-to-value ratio ($SLTV$) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $SLTV_{it} \in (l_k, h_k)$, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents job mobility that does not involve geographic mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

	Within-ZIPcode Mobility	
	(1)	(2)
$\mathbf{1}_{\{0<LTV<0.7\}}$	-0.0003	
	(0.0002)	
$\mathbf{1}_{\{0.8\leq LTV<1\}}$	-0.0002	
	(0.0004)	
$\mathbf{1}_{\{1\leq LTV<1.4\}}$	0.002**	
	(0.001)	
$\mathbf{1}_{\{1.4\leq LTV\}}$	0.002**	
	(0.001)	
$\mathbf{1}_{\widehat{\{0<LTV<0.7\}}}$		-0.0001
		(0.0004)
$\mathbf{1}_{\widehat{\{\mathbf{0.8\leq LTV<1}\}}}$		-0.0003
		(0.001)
$\mathbf{1}_{\widehat{\{\mathbf{1.0\leq LTV<1.4}\}}}$		0.002**
		(0.001)
$\mathbf{1}_{\widehat{\{\mathbf{1.4\leq LTV}\}}}$		0.004**
		(0.002)
Tenure Controls	Yes	Yes
Individual FE	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes
Observations	13,389,609	13,389,609
R^2	0.388	0.388

Table 11: Robustness : Different LTV values at Origination & Interest Rates

This table reports the coefficient estimates from the following IV regressions that estimate the effect of LTV on labor mobility where we assume different values of LTV at origination and interest rates:

$$1_{\{l_k \leq LTV_{it} < h_k\}} = \delta_i + \delta_{zt} + \delta_{ct} + 1_{\{l_k \leq SLTV_{it} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k 1_{\widehat{\{l_k \leq LTV_{it} < h_k\}}} + X_{it}\gamma + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq LTV_{it} \leq h_k\}}$ ($1_{\{l_k \leq SLTV_{it} \leq h_k\}}$) indicate different LTV (SLTV) value buckets which turn on when the loan-to-value (synthetic loan-to-value) ratio of an individual's primary residence at the end of month t is between l_k and h_k, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents different measures of mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

Panel A : LTV at Origination Values				
	Mobility (1)	Mobility (2)	Mobility (3)	Mobility (4)
$\mathbf{1}_{\{0<\widehat{LTV}<0.7\}}$	0.001**	0.002***	0.002***	0.001**
	(0.0005)	(0.0003)	(0.0004)	(0.0005)
$\mathbf{1}_{\{\widehat{\mathbf{0.8 \leq LTV}}<\mathbf{1}\}}$	0.0004	0.00002	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
$\mathbf{1}_{\{\widehat{\mathbf{1.0 \leq LTV}}<\mathbf{1.4}\}}$	-0.003***	-0.004***	-0.002***	-0.003***
	(0.001)	(0.0005)	(0.0005)	(0.001)
$\mathbf{1}_{\{\widehat{\mathbf{1.4 \leq LTV}}\}}$	-0.003**	-0.003***	-0.002**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
LTV at Origination	0.70	0.75	0.80	Conditional on no of Mortgages
Tenure Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
ZIPcode$\times$Month FE	Yes	Yes	Yes	Yes
Purchase cohort$\times$Month FE	Yes	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609	13,389,609
R^2	0.172	0.172	0.172	0.172

Table 11 (contd)

Panel B : Interest Rate Values					
	Mobility	Mobility	Mobility	Mobility	Mobility
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}_{\widehat{\{0<LTV<0.7\}}}$	-0.0001	-0.00001	0.001*	-0.00004*	0.0001
	(0.00004)	(0.00003)	(0.0003)	(0.00002)	(0.0001)
$\mathbf{1}_{\widehat{\{\mathbf{0.8 \leq LTV < 1}\}}}$	-0.00005	-0.00003	0.0004	-0.00002	0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.00004)	(0.0001)
$\mathbf{1}_{\widehat{\{\mathbf{1.0 \leq LTV < 1.4}\}}}$	-0.001***	-0.003**	-0.002**	-0.003**	-0.001***
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.0004)
$\mathbf{1}_{\widehat{\{\mathbf{1.4 \leq LTV}\}}}$	-0.0005	-0.0002	-0.003**	-0.0002	-0.001**
	(0.0004)	(0.0003)	(0.001)	(0.0002)	(0.0004)
Interest Rate	5.75%	6.25%	6.25%	7.25%	7.75%
Tenure Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
ZIPcode×Month FE	Yes	Yes	Yes	Yes	Yes
Purchase cohort×Month FE	Yes	Yes	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609	13,389,609	13,389,609
R^2	0.227	0.241	0.241	0.195	0.197

Table 12: Robustness : MSA & State Level Mobility

This table reports the coefficient estimates from the following IV regressions that estimate the effect of LTV on labor mobility where we assume different values of LTV at origination and interest rates:

$$1_{\{l_k \leq LTV_{it} < h_k\}} = \delta_i + \delta_{zt} + \delta_{ct} + 1_{\{l_k \leq SLTV_{it} < h_k\}} + X_{it}\gamma + \epsilon_{iczt}$$

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k 1_{\widehat{\{l_k \leq LTV_{it} < h_k\}}} + X_{it}\gamma + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode× month fixed effects, δ_{ct} are purchase cohort×month fixed effects, the indicator functions, $1_{\{l_k \leq LTV_{it} \leq h_k\}}$ ($1_{\{l_k \leq SLTV_{it} \leq h_k\}}$) indicate different LTV (SLTV) value buckets which turn on when the loan-to-value (synthetic loan-to-value) ratio of an individual's primary residence at the end of month t is between l_k and h_k, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket (0.7.0.8] as base for comparison. The dependent variable y_{iczt} represents different measures of mobility. Standard errors are clustered on two dimensions at the individual and month level, and are reported in the parantheses below the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respecitively.

	MSA Level Mobility			State Level Mobility		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}_{\widehat{\{0<LTV<0.7\}}}$	0.0002***	0.0001**	0.0001***	-0.0001	-0.00001	-0.00004*
	(0.00005)	(0.00004)	(0.00003)	(0.00004)	(0.00003)	(0.00002)
$\mathbf{1}_{\widehat{\{0.8\leq LTV<1\}}}$	-0.0001	-0.0001	-0.0001	-0.00005	-0.00003	-0.00002
	(0.0001)	(0.0001)	(0.00004)	(0.0001)	(0.0001)	(0.00004)
$\mathbf{1}_{\widehat{\{1.0\leq LTV<1.4\}}}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.0003**	-0.0003**
	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0001)	(0.0001)
$\mathbf{1}_{\widehat{\{1.4\leq LTV\}}}$	-0.001	-0.0003	-0.0003	-0.0005	-0.0002	-0.0002
	(0.001)	(0.0004)	(0.0002)	(0.0004)	(0.0003)	(0.0002)
Tenure Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIPcode×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Purchase cohort×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,389,609	13,389,609	13,389,609	13,389,609	13,389,609	13,389,609
R^2	0.229	0.247	0.186	0.227	0.241	0.195

Figure 1: Distribution of Individuals Across States as of Jan, 2010

This figure compares the distribution of individuals in our sample across states in the U.S. to the same distribution of entire population (as of 2010) based on location of residence. The numbers in the figure represent percentage difference in this distribution, i.e. $\frac{SamplePopulation_s}{TotalPopulation_s} - \frac{SamplePopulation}{TotalPopulation}$.

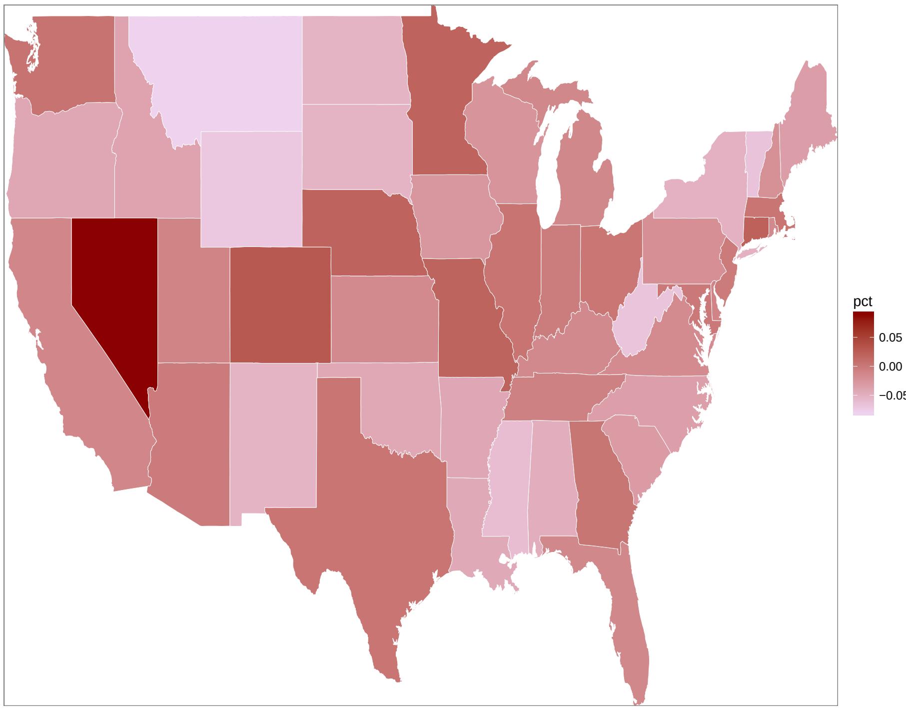


Figure 2: Purchase Year Distribution

This figure illustrates the distribution of purchase year in our sample. The horizontal axis represents year while the vertical axis represents the number of purchases.

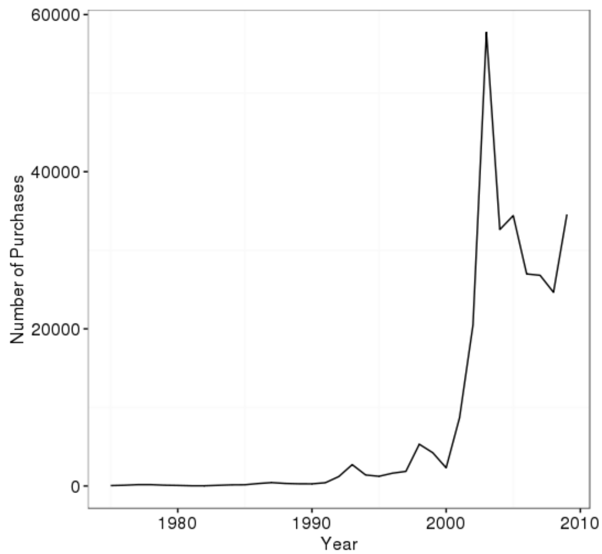
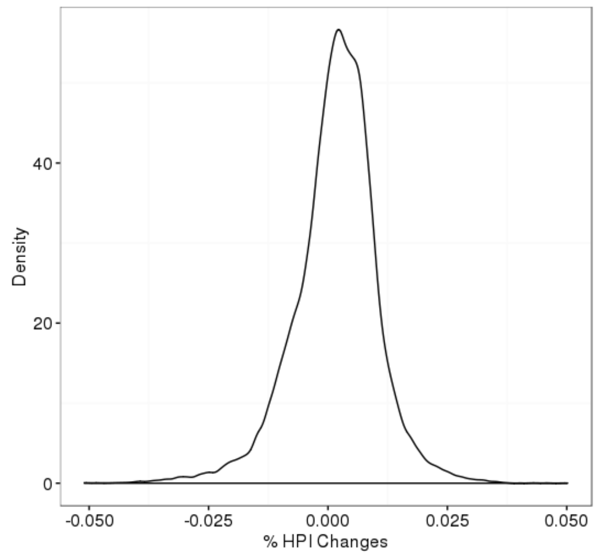
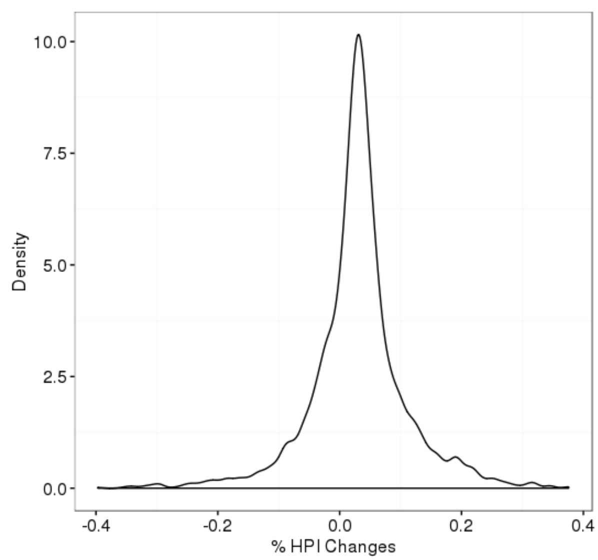


Figure 3: HPI Changes

This figure illustrates the distribution of monthly and annual changes in house price index (HPI). The plots suggest that there is ample variation in HPI during our sample period.



(a) Monthly HPI Changes



(b) Annual HPI Changes

Figure 4: Distribution of Individuals with Negative Home Equity Across States as of Jan, 2010

This figure illustrates the distribution of individuals having negative home equity as of Jan, 2010 across states in the U.S. based on location of their residence.

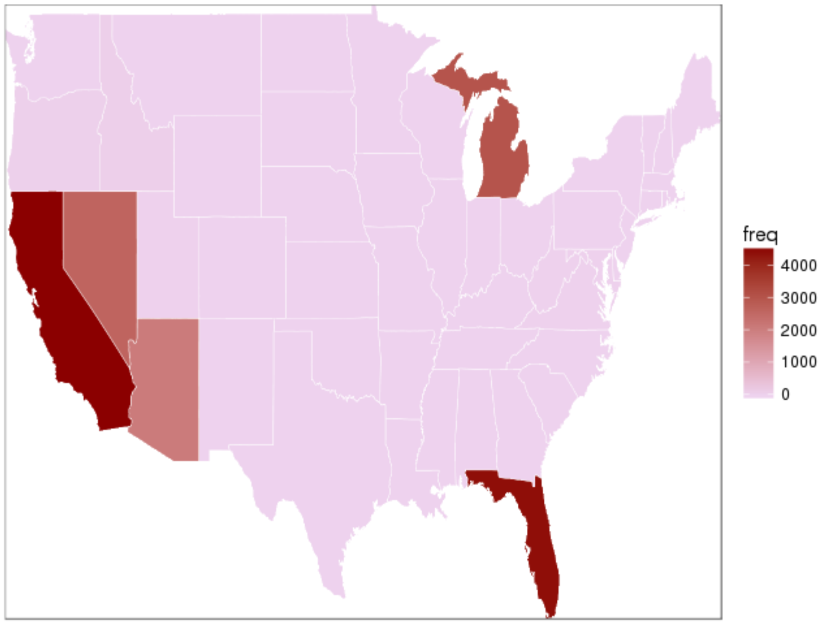
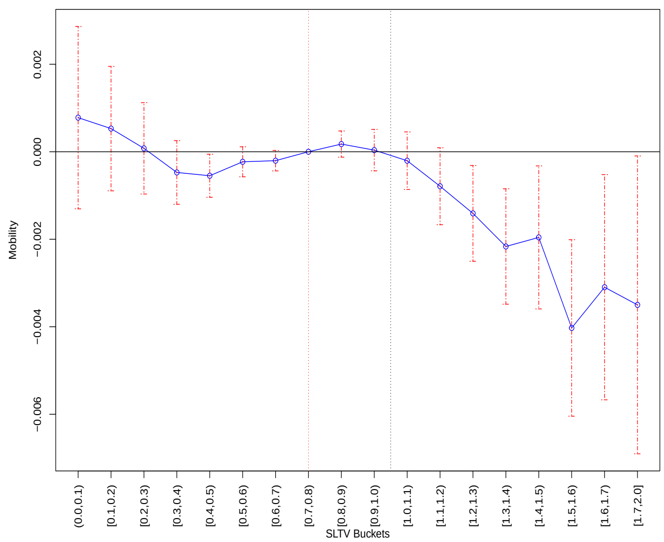


Figure 5: Home Equity & Mobility

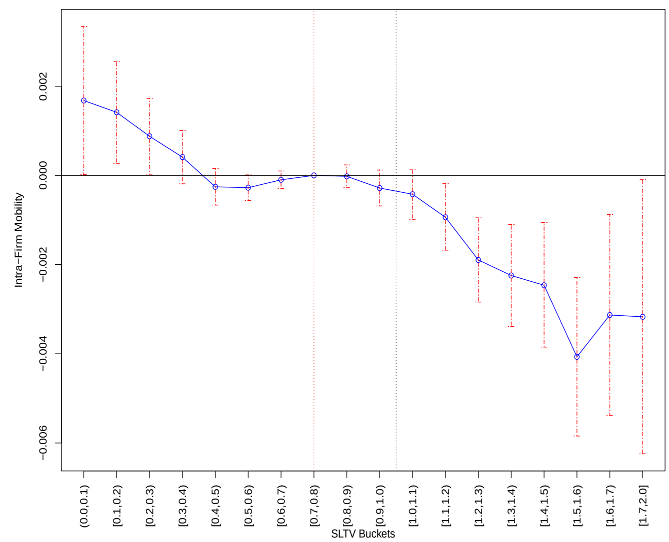
This figure plots the coefficient estimates from the following reduced form regressions that estimate the effect of SLTV on labor mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \leq SLTV_{it} \leq h_k\}} + \gamma \times X_{it} + \epsilon_{iczt}$$

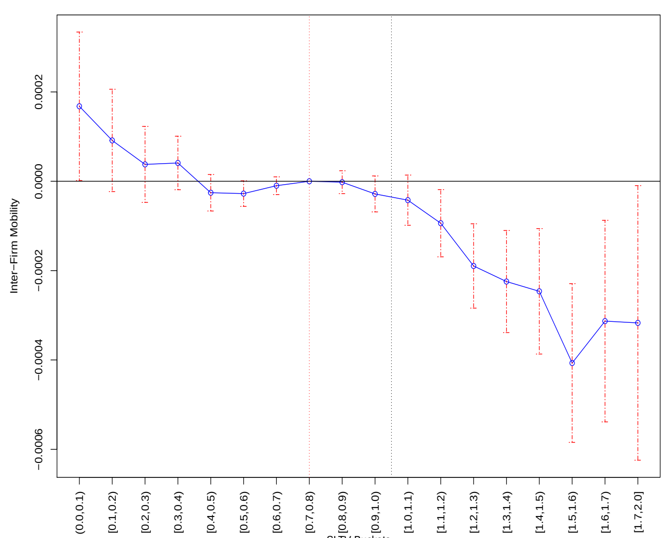
where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \leq SLTV_{it} \leq h_k\}}$ indicate different SLTV value buckets which turn on when the synthetic loan-to-value ratio ($SLTV$) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $SLTV_{it} \in (l_k, h_k)$, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket $(0.7.0.8]$ as base for comparison. The dependent variable y_{iczt} represents different measures of mobility. Standard errors are clustered on two dimensions at the individual and month level, and the corresponding confidence intervals are plotted.



Panel (a) Mobility



Panel (b) Intra-Firm Mobility



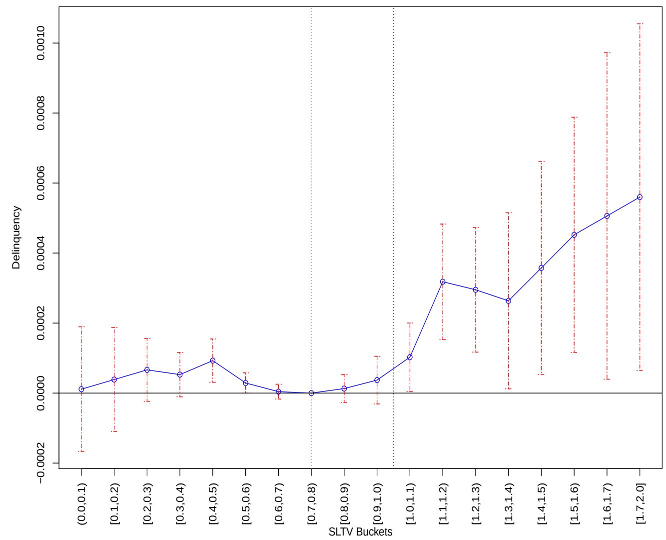
Panel (c) Inter-Firm Mobility

Figure 6: Home Equity, Delinquency & Mobility

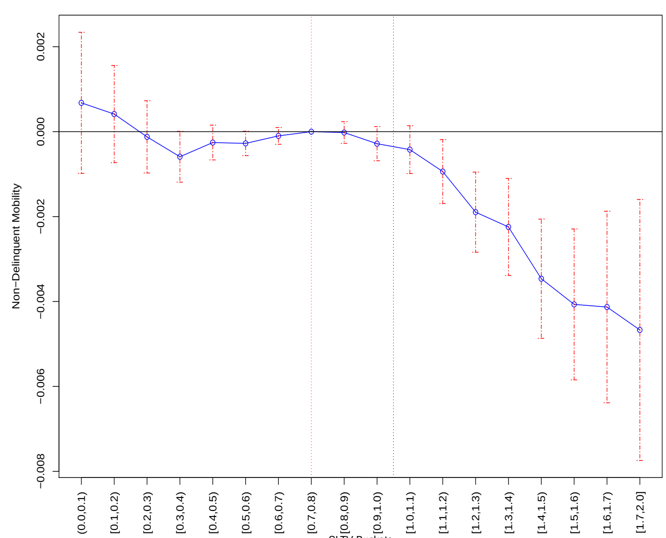
This figure plots the coefficient estimates from the following reduced form regressions that estimate the effect of SLTV on delinquency and non-delinquent mobility:

$$y_{iczt} = \delta_i + \delta_{zt} + \delta_{ct} + \sum_k \beta_k \times 1_{\{l_k \le SLTV_{it} \le h_k\}} + \gamma \times X_{it} + \epsilon_{iczt}$$

where the subscript i refers to the individual, c, the purchase cohort to which the individual belongs based on when she bought her house, z, the ZIPcode where the individual resides and t is time in year-month, δ_i are individual fixed effects, δ_{zt} are ZIPcode$\times$ month fixed effects, δ_{ct} are purchase cohort$\times$month fixed effects, the indicator functions, $1_{\{l_k \le SLTV_{it} \le h_k\}}$ indicate different SLTV value buckets which turn on when the synthetic loan-to-value ratio ($SLTV$) of an individual's primary residence at the end of month t is between l_k and h_k. i.e., $SLTV_{it} \in (l_k, h_k)$, and X_{it} are quadratic controls for individual's tenure at the firm. We exclude LTV bucket $(0.7.0.8]$ as base for comparison. The dependent variable y_{iczt} represents measures of delinquency and non-delinquent mobility. Standard errors are clustered on two dimensions at the individual and month level, and the corresponding confidence intervals are plotted.



Panel (a) Delinquency



Panel (b) Non-Delinquent Mobility