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# Individual and Local Effects of Unemployment on Mortgage Defaults

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## Abstract

Using survey data from the Panel Study of Income Dynamics, we document descriptively that unemployment has a relatively large effect on individual mortgage default rates: The average default rate for the employed is 2.4%; whereas for the unemployed, it is 8.5%. Once several other characteristics are controlled for, the unemployed have default rates that are 4 percentage points larger than those of the employed; and when endogeneity is additionally accounted for, the unemployment effect on default rates declines to 3 percentage points. Moreover, we find that more granular metrics for unemployment entail lower comparable effects of unemployment on default rates. That is, the comparable effect of individual unemployment on mortgage defaults is rather lower than the effect of state or county unemployment rates. This finding suggests that local metrics of unemployment, rather than attenuating possibly large individual unemployment effects on defaults, indeed contain more information than the aggregation of these individual effects.

*Keywords:* mortgage debt, mortgage default, unemployment, consumer credit

*JEL Classification:* G21, R31, J64

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## 1. Introduction

In this paper, we estimate the effects on mortgage defaults of local unemployment rates and individual unemployment. We find that the individual effect of unemployment on mortgage defaults is lower than the commensurable effects of state or county unemployment rates on defaults. When endogeneity of individual unemployment is accounted for, the sensitivity of mortgage defaults to unemployment is even lower. This finding suggests that more granular metrics of unemployment entail lower comparable estimated effects on mortgage default. Local unemployment rates are likely to reflect macroeconomic effects that exceed the mere sum of individual unemployment effects. This is important, as deteriorating economic conditions are reflected in increased local unemployment rates, the job loss of surrounding individuals, which affect individuals who do not directly suffer unemployment shocks.

The literature on this subject has converged in recent years to explaining defaults by "double triggers" that combine deteriorations of both equity and liquidity positions. Research by Kau et al. (1993) and Deng, Quigley, and van Order (2000) emphasizes the importance of deteriorated equity on defaults. Mortgage debt is conceived of as a put option on equity, so that borrowers default when the debt value exceeds the value of the collateral by a sufficient amount. More recent work by Elul et al. (2010), Foote et al. (2009), Campbell and Cocco (2015), Fuster and Willen (2013), and Calem and Sarama (2017) additionally remarks on the importance of deteriorations of liquidity positions, in particular monthly payment capacity. Many borrowers remain current even when the debt value exceeds the value of the house. Financial stress contained in the difficulty of pulling together a mortgage payment also plays a significant role in defaults (Foster and Van Order (1984) and Bhutta et al. (2010)). Borrowers may not be able to wait for a house value recovery (Kau et al. (1993)) if they cannot even make a mortgage payment (Elmer and Seelig (1999), Bajari et al. (2008), and Gerardi et al. (2018)).

Borrowers who lose their jobs and suffer a reduction in income also face a liquidity shock, which makes meeting mortgage payment obligations more difficult.[1] The unemployment effect on defaults, however, has been found to be relatively weak (Mayer et al. (2009)) and Haughwout et al. (2008)). Gyourko and Tracy (2014) contend that this small effect is actually the

[1] Unemployment is the most predictive variable for mortgage interest rates and preforeclosure filing rates (Doviak and MacDonald (2012)); higher unemployment insurance payouts reduce the rate of foreclosure by supporting payments (Hsu et al. (2018)).

result of underestimating the underlying unemployment effect, an “attenuation bias” or a measurement error introduced by using local unemployment rates as proxies for individual unemployment explanatory variables that are unavailable in many data sets. Gerardi et al. (2018) overcome this problem by using individual level data to find evidence of strategic defaults by determining if borrowers with high loan-to-value (LTV) ratios and sufficient income to cover payments were defaulting on their mortgages. They find that becoming unemployed increases default rates by 5 to 13 percentage points from the average sample default rate of 3.9%.

Our study is closest in methodology to Gerardi et al. (2018), in that we leverage panel data to answer questions regarding mortgage default and income/employment at the individual level. We exploit the rich sociodemographic data of the Panel Study of Income Dynamics (PSID), a longitudinal household survey that began in 1968 with more than 18,000 individuals and 5,000 families, which has a variety of characteristics including the income, employment status, and mortgage data of individual household members. These data allow us to control for various important social demographics such as education, race, and sex, as well as standard financial indicators, to isolate the impact of individual employment status.

This paper contributes to the existing literature on mortgage defaults by showing that the effect of local unemployment rates is stronger than the comparable individual effect. The unemployment of an individual has a large effect on their mortgage default rates, between 2 and 3 percentage points from an average default rate of 2.7% (that would be an increase of between 74% and 111%). To determine an economywide effect that is comparable to an increase of 1 percentage point in the unemployment rate of a population, we compute 2 percentage points times 1%; that is, 2 x 0.01=0.02 percentage points. Thus, if an additional 1% of the population becomes unemployed, mortgage defaults increase by less than the estimated effect of a 1% increase in state or county unemployment rates. This individual unemployment effect is found to be stronger for increased macroeconomic and individual financial stress, right after the Great Recession and for high individual combined loan-to-value (CLTV) ratios. We also show that various other types of liquidity sources, such as having savings accounts, decrease default rates substantially.

The rest of this paper is organized as follows. In the next section, we describe the PSID and the sample selection, and in Section 3, we discuss descriptive statistics. In Section 4, we present our main results on the effect of unemployment on defaults. Section 5 extends these results to account for endogeneity, and Section 6 summarizes the main conclusions of this paper. Additional relevant material is presented in the Appendix.

## 2. Data

The PSID data are a panel in which the same households are tracked over time and information regarding the head of household, spouse, if applicable, and other household members are recorded. The information is survey data in which respondents self-report the answers to various fixed questions once every two years. The main advantage of this data set is that there are characteristics not typically included in mortgage data sets such as sociodemographics and detailed employment data**,** both for the current year and the previous year. We can also observe the individual's income over time as well as income for the entire household. As the head of household is presumed to be responsible for paying down household debts, we will restrict our attention to these individuals.

We are interested in the period 2009–2017, which includes the Great Recession. Because the PSID introduced the variable that tracks mortgage defaults only in 2009, we are left with five years of study: 2009, 2011, 2013, 2015, and 2017. We limit our analysis to individuals in the PSID who are heads of households with ages reported between 24 and 65 and who reported having a mortgage during that period. For the 2009–2017 time frame, these restrictions take the starting 143,671 observations down to 12,268. This important downsize occurs because in this panel of individuals we consider only heads of households and mortgage holders. In Appendix A, we give further details about this sample selection.

Our measure of defaults is based on the variable introduced in 2009 that reports how many months the borrower was behind on mortgage payments in the previous year as of the interview date. A default is defined as being at least 60 days behind on the first mortgage.

We construct a CLTV based on the total of the primary and secondary mortgage as the combined loan amount[2] and a debt-to-income (DTI) variable by taking the annual income of the household and dividing it by the monthly mortgage payment multiplied by 12.

[2] In Appendix C, we detail the trends in the data, in particular, the trend in percentages of homeowners with first and second mortgages.

The PSID records a variety of employment data for the head of household, which include the total income earned by the head over the previous year. We can track up to the four most recent jobs the household head held since the previous interview date, as well as the self-reported employment status of the head. Additionally, the head reports the number of months of unemployment in the previous year.

Several studies have verified how representative the PSID is of the U.S. population by comparing the main variables' statistics with other sources of data. We have comparisons of the PSID with the Survey of Consumer Finance (SCF) (Gerardi et al. (2018), Pfeffer et al. (2016), Cooper et al. (2019), with the American Household Survey and McDash/Equifax data (Gerardi et al. (2018)). We also corroborate the representativeness of the PSID mortgage data by showing that the PSID values of mortgage characteristics are similar to those reported by the Bureau of Labor Statistics (BLS) in its Current Population Survey (CPS). Appendix B provides details of this comparison.

## 3. Descriptive Statistics

This section discusses some basic features of data, with specific attention to the connection between unemployment and mortgage defaults. In Table 1, we compare the mortgage holding population to the non-mortgage holding population. Mortgage holders are more likely to be White, while Blacks were the least likely to hold a mortgage when segmenting by race. The mortgage holders also have more years of formal education and higher incomes than non-mortgage holders. The education levels are relatively high; around 70% of observations had more than a high school degree. The marriage rate among mortgage holders is noticeably higher, with around 40% of non-mortgage holders being unwed as of reporting compared with 11% for mortgage holders.

[Table 1 here]

For mortgage holders, heads of household are primarily male due to the reporting definition in which the default assumption is that the head is the male in a couple unless certain exception criteria are met. This labeling scheme contributes to female heads rarely being reported as married and mostly being unwed or divorced, yet around 75% of the heads are presently married. Around 10% of all borrowers who hold a mortgage are divorced. Heads who are currently married exhibit significantly lower default rates than any other marital statuses. Around 5% of household heads report a period of unemployment in the previous year.

In Table 1, we also see on average significant contributions to income from other household members, with the average total income per household being significantly higher than the average head of household income. The mean household income was between 1.5 and 2 times the mean head income.

Even though the PSID does not include any measure of credit score, it does include a detailed breakdown of the borrower's financials including debt by product type, as well as information regarding the borrower's available capital. We observe that most borrowers have some available savings, but around 30% have retirement savings.

[Table 2 here]

In Table 2, we present the available information of mortgage characteristics contained in the PSID. These are relatively young mortgages, with an average loan term of around 25 years at origination and 20 years remaining currently, with around $275,000 in house value at origination and $245,000 in current value. The CLTV is around 70% at an interest rate of around 4.7%, which corresponds to a monthly payment of $1,200. These characteristics reflect very standard mortgages as corroborated by other data sets on mortgages.

[Table 3 here]

We next examine descriptive evidence for the effect of unemployment on mortgage defaults. In Table 3, we show default rates for the whole sample and for the unemployed, as well as the unemployment rate by individual attributes. Very clearly, the unemployed experience heightened the risk of default in comparison to the whole sample. The default rate for the whole sample is 2.66%, while the default rate for the employed is 2.35% and for the unemployed, 8.54%, with a sample unemployment rate of 4.96%. This is a difference of default rates of 6.2 percentage points, or 360%, between the unemployed and the employed. This pattern repeats itself across a variety of social and economic variables. The groups most strongly affected by the unemployment shock were, unsurprisingly, individuals with lower income and with less education, supporting the notion that the unemployment shock more strongly impacts economically vulnerable individuals. We also see that this shock hits more strongly those who are not White, women, and the unmarried, as well as younger people. On the other hand, the difference in default rates between the employed and the unemployed cannot be considered a causal effect. Yet, the higher rates suggest that unemployment is associated with default, especially for borrowers who are not married, not White,[3] female, younger, less educated, or in a lower-income bracket.

We have, so far, a "raw" gap of 6.2 percentage points as the difference in default rates between the unemployed. In the next section, we will see that once we control for sociodemographic and financial attributes, and we further account for endogeneity of unemployment, the difference in default rates conditional on employment status is lower.

Besides regular income flows received when employed, a borrower may have access to several potential sources of liquidity prior to being completely incapable of paying. In the PSID, we also have data on liquidity: amount of liquid assets, presence of savings accounts, and size of retirement accounts. We label borrowers as "having liquid assets," if they report having at least $1,000 in liquid assets.

[Table 4 here]

The conditional default probabilities based on types of available liquidity are found in Table 4. Lacking liquid assets, savings, or IRAs implies a significant rise in default likelihood, with IRA accounts being the least common form of savings but having the lowest risk. Lacking $1,000 in liquid assets results in the largest difference in default likelihood, 7 percentage points, with around one out of four borrowers being subject to this vulnerability.

## 4. The Sensitivity of Mortgage Default to Unemployment

In this section, we discuss the sensitivity of defaults to unemployment. In Table 5, we report a linear probability model estimation for mortgage default with different measures of unemployment at the state, county, and individual level. State- and county-level unemployment rates by year come from the Bureau of Labor Statistics;[4] they enter the estimation in levels and annual variations, while individual unemployment is a binary variable. There are also several

[3] This evidence is consistent with the existing literature that notes that Black individuals are disproportionately likely to hold subprime mortgages (Calem et al. (2004), Bunce (2000)); and exhibit higher default rates than White individuals (Doviak and MacDonald (2012)).

[4] Some of the data used in this research are derived from Restricted Data Files of the Panel Study of Income Dynamics, obtained under special contractual arrangements designed to protect the anonymity of respondents. These data are not available from the authors. Those interested in obtaining PSID Restricted Data Files should contact PSIDHelp@umich.edu. We merged public PSID data with *Corelogic Solutions* HPI county level data by accessing the confidential PSID geocode data obtained under the aforementioned contractual arrangement.

control variables: annual variation of the *Corelogic Solutions* Home Price Index (HPI); CLTV; DTI; variables for liquidity; variable interest rate; and sociodemographic variables, such as education, sex, race, age, and marital status.[5]

[Table 5 here]

The effect of a 1% increase in state and county unemployment measured in levels on defaults is 0.16 and 0.10 percentage points, respectively, with a better fit for state over county measures. That is, in terms of goodness of fit, more granular is not necessarily better. It is also remarkable that the level of state unemployment performs better than its annual variation; whereas the variation of county unemployment performs better than its level, with a larger effect of 0.22 percentage points.

When individual unemployment is introduced instead, the overall fit of the estimation improves, but the effect is smaller in comparative terms than county- or state-level effects: A 1% increase in the unemployment rate implies a 0.04 percentage point increase in the default rate. This effect is obtained from the estimated individual effect: When one individual becomes unemployed, their individual default rate increases by 4 percentage points; when 1% of individuals becomes unemployed, their default rate increases by 4 basis points.

This individual increase of 4 percentage points from an average default rate of around 2.7% is relatively large, yet lower than the implied 6.2 percentage point raw and uncontrolled individual effect that we see in the descriptive statistics.[6]

To account for the unemployment effect during times of stress, we also include two interaction terms: unemployed in year 2009, when the Great Recession was still present, and unemployed during the 2009 observation with high CLTV. With this, the unemployment effect declines to 3.3 percentage points, but increases by 3 percentage points for being unemployed in 2009 and by 8 percentage points for being unemployed in 2009 under financial distress, as

[5] We also performed this same regression, but without including sociodemographic variables, as it would be done in the financial data sets that are generally available for stress testing purposes, which typically do not include individual traits. The results for that specification are not substantially different than the results shown in Table 5. We also perform a similar estimation but with Probit and Logit specifications. In Appendix D, we report and discuss the marginal effects of a Probit specification.

[6] The individual measure of unemployment comes certainly from a different source, the PSID, than the local unemployment measure, which comes from the BLS. The aggregation of individual unemployment variable at the state level exhibits a clear positive correlation with state unemployment: 0.22, 0.15, 0.21, 0.40, and 0.19 in 2009, 2011, 2013, 2015, and 2017, respectively. We performed the same estimations with lagged state and county unemployment rates, but the results did not change substantially. Thus, the different results for different metrics of unemployment do not arise from lagged variables.

captured by the high CLTV. Unemployment for individuals with financial distress under a stress scenario can experience an approximately 14 percentage point rise in the likelihood of default. These effects do not vary substantially whether a specification contains state or county HPI variations; however, the fit is better with a state HPI measure.

These estimations indicate that a 1 percentage point increase in the level of the state unemployment rate is associated with an increase in the default rate of 0.16 percentage points. A 1 percentage point increase in the change of the state unemployment rate with respect to last year's state unemployment rate is associated with an increase of 0.12 percentage points in the default rate. These two effects become 0.10 and 0.22, respectively, for the county unemployment rate. On the other hand, an increase of 1 percentage point in the proportion of individuals who are unemployed in our sample increases the average mortgage default rate by 0.04 percentage points. With more granular measures, unemployment has weaker effects on default rates. This result suggests that the "attenuation" happens in the opposite direction of what was expected or, said differently, that aggregation into larger geographical units amplifies the effect of unemployment. This pattern indicates that local unemployment rates are likely to contain more information than individual unemployment rates, such as a deteriorating macroeconomic environment that also affects individuals who do not suffer job loss or credit supply that is conditioned on public indicators of unemployment.

These results also illustrate the double trigger effect on defaults — that is, besides the financial position of borrowers, the liquidity position also matters for triggering default. Liquid assets and IRA savings appear to be highly significant. Moreover, the effect of liquid assets is relatively large: Having liquid assets — that is, more than $1,000 — reduces the probability of default by 4.6 percentage points.

In sum, with more granular measures of unemployment, we observe a better estimation performance but a lower comparable effect on the average mortgage default rate.

## 5. Accounting for Endogeneity of Unemployment

Because unemployment and default on a loan may be jointly determined by several other factors, rather than unemployment immediately provoking default, the previous estimations of defaults on unemployment may be biased. We correct for this endogeneity by an Instrumental Variable estimation with two instruments: welfare transfers and unemployment compensation. The identifying assumption here is that these variables are excluded from the mortgage default estimation, increase the probability and duration of unemployment, and only *indirectly* influence mortgage defaults, just over its effect on alleviating the loss of income caused by unemployment.

We perform two estimations, one with and one without unemployment compensation. In the sample, 2.8% were unemployed and did not receive unemployment compensation, 2.1% were unemployed and received unemployment compensation, and 2.2% were employed and did receive unemployment compensation. That is, this is not a variable that would perfectly predict unemployment.

We also consider the approach by Gyourko and Tracy (2014), who simulated individual unemployment histories based on historical transition rates and local unemployment. Their claim was that simulated individual unemployment had a larger effect on default rates than local unemployment rates. In our case, by using the PSID, we do not need to predict or simulate individual unemployment because we have access to the true unemployment status for each borrower and more granular measures of marketwide unemployment rates, state- and county-level unemployment rates. Applying their procedure to our data can be considered a particular form of IV estimation where geographic unemployment rates remove idiosyncratic variations from individual unemployment fluctuations.

[Table 6 here]

In Table 6, we report linear probability estimations of individual unemployment. We have one version with only welfare transfers and one version that additionally includes unemployment compensation as an explanatory variable. Both of them include sociodemographic data available in the PSID. Very clearly, the estimation fit improves substantially when unemployment compensation is included. The estimation a la Gyourko and Tracy (2014) unsurprisingly exhibits a low predictive power, as it contains only one explanatory variable.

[Table 7 here]

In Table 7, we present the results of the estimation that accounts for endogeneity. What we learn from this exercise is that using a weak instrument delivers very large effects of individual unemployment on mortgage defaults. However, with a better instrument — that is, one which exhibits a larger correlation with unemployment while no direct correlation with defaults, such as unemployment compensation — the sensitivity of mortgage defaults to unemployment is only 3 percentage points for an individual who becomes unemployed, or 3 basis points for an increase of 1 percentage point in the unemployment rate, that is, lower than the OLS estimated effects. Consequently, accounting for endogeneity implies a lower sensitivity of mortgage defaults to unemployment. Yet, when the interaction of unemployment with economic and individual financial distress is considered, the total sensitivity becomes very large, reaching more than 37 percentage points at an individual level and 0.37 for a 1% change in the unemployment rate, which is much larger than its OLS counterpart of up to 13 percentage points altogether, and 0.13 percentage points for a 1% change in the unemployment rate.

We also perform an exercise like Gyourko and Tracy (2014). We observe that the size of the coefficient of predicted unemployment status is fairly large. However, although the predictive power observed by this regression is similar to theirs, they are not directly comparable, as these authors measured the risk of default at the monthly level, while the PSID is biennial. We interpret these large results as being driven by weak instruments. Once a stronger instrument is used, as in the previous estimations, we observe that the estimated effect of individual unemployment is lower than by an OLS estimation. However, these results are in line with the previous finding that more granular metrics of unemployment imply lower effects of unemployment on default rates: The plain individual unemployment effect is lower than the individual unemployment effect that is "instrumented" with local unemployment rates. This is indicative that the individual variation in unemployment lowers the estimated sensitivity of mortgage default rates to unemployment.

In sum, accounting properly for endogeneity of unemployment reduces the estimated effect of unemployment on defaults. Moreover, when there is economic and individual financial distress, accounting for endogeneity increases it substantially at the individual level. We also find that more granularity in measuring unemployment implies lower effects of unemployment on default rates.

**6. Conclusion**

In summation, using survey data from the PSID, we observe that the unemployed register a default rate that is 6.1 percentage points above the default rate of the employed. Once we control for several sociodemographic and economic factors, we find that individual unemployment is a better predictor but has a lower comparable effect on mortgage default rates than state and county unemployment. We also find that the individual unemployment effect is larger during periods of macro stress and for borrowers with a high CLTV. These results corroborate that besides the financial position of borrowers, the liquidity position also matters for triggering default. In that same line, we also find that liquidity holdings by the borrower, mainly liquid assets, but also savings and IRA accounts, alleviate financial stress and reduce individual mortgage default rates by around 4 percentage points.

We estimate that individual unemployment increases individual default rates by around 4 percentage points, and by 3 percentage points if endogeneity is accounted for, which is large compared with the default rate of 2.4% by the employed. However, if 1% of these individuals becomes unemployed, the average default rate increases by only 3 or 4 basis points, which is considerably lower than the 10 basis point increase in default rates from a 1% increase in the state or county unemployment rates.

This suggests that local unemployment rates contain more information than the sum of individual unemployment statuses, such as the externality of a macroeconomic unemployment shock on individuals who do not suffer job loss. Estimating mortgage defaults with local unemployment rates, rather than attenuating a possibly large individual unemployment effect, is likely to consider this externality on defaults.

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**Appendix A: Sample Selection**

As mentioned previously, the data set includes entries for multiple persons in the same household under the same head. We use the relation to head field to identify the actual head of household and include only their observations to avoid double counting. Additionally, a head would be removed from the pool if less than $1,000 of principal was reported or the CLTV (accounting for first and second mortgages) exceeded 250%.

Heads were also removed from our analysis if no information about sociodemographic, financial, or mortgage characteristics was reported. Some observations were also removed if the total household income reported was smaller than the reported income earned by the household head.

Table A1: Selection process

| Criteria | Observations |
|---|---|
| All (2005-2017) | 210,703 |
| Only Heads | 61,606 |
| Age: 24-65 | 50,735 |
| Social Demographics: Non-missing | 49,150 |
| Finacial Variables: Non-missing | 46,225 |
| Household Income>=Head Income | 45,197 |
| No Mortgage | 26,350 |
| Homeowner | 4,720 |
| Non-Homeowner | 21,630 |
| Mortgage Holder | 18,847 |
| Only 2009-2017* | 13,381 |
| Mortgage Variables: Non-Missing | 13,096 |
| CLTV=<2.5 & Outstanding>=1000 | 12,507 |
| Has Valid State | 12,475 |
| Not Continuing Default [final sample] | 12,268 |
| Defaulted | 326 |
| Current | 11,942 |

*years selected as delinquency variable first implemented in 2009

Source: PSID.

**Appendix B: Representativeness of the PSID**

To assess the relative size of the PSID compared with the overall mortgage market and the veracity of responses by borrowers who intentionally underreport negative news, we examine the comparability of statistics generated using the PSID data to other reputable sources.

Regarding the robustness of variables, we consider all household heads including non-mortgage holders to effectively compare the PSID values with available measures.

Table B1: Median Annual Income for All Heads by Education Level for 2017

| Education | PSID* | CPS** |
|---|---|---|
| Less than a high school diploma | 28000 | 27040 |
| High school diploma, no college | 38000 | 37024 |
| Between high school and bachelor's (Some college for CPS) | 40000 | 40248 |
| Bachelor's degree | 60000 | 60996 |
| More than bachelor's (master's for CPS) | 67500 | 72852 |

*Only includes incomes between $10000-$1000000 for PSID

**CPS provides weekly earnings. We multiply by 52 to approximate annual

We compare respondent income and unemployment by education level in the PSID to those produced by the Bureau of Labor Statistics (BLS) in its Current Population Survey (CPS). Here we restricted annual incomes between $10,000 and $1,000,000; this range was chosen primarily to omit wages that could not reflect a full-time annual salary and also to cull outliers. After implementing this restriction, the median income by education level generally matched the BLS numbers from the CPS for 2017. At all education levels excluding master's and above, the medians were within $1,000. For the master's level, the BLS numbers were generally greater than those observed in the PSID. Mortgage holders in the PSID generally earned more than non-mortgage holders even with the same level of educational attainment.

When using the survey response for whether respondents had a period of unemployment in the previous year, the unemployment rates observed were relatively high. This is likely caused by the PSID looking back for unemployment during the entire previous year while conventional unemployment rates are point-in-time measures. Because of this, we restricted our comparison to the proportion of borrowers who reported being unemployed at least one month in the previous year to better capture persistent unemployment. After updating our definition of unemployment, the rates of unemployment were comparable between the PSID and CPS for most education levels; however, we did observe noticeably higher rates of unemployment in the PSID for borrowers without a high school education.

Table B2: Unemployment Rate for All Heads by Education Level for 2017

| Education | PSID* | CPS |
|---|---|---|
| Less than a high school diploma | 8.71 | 6.50 |
| High school diploma, no college | 4.73 | 4.60 |
| Between high school and bachelor's (Some college for CPS) | 3.53 | 4.00 |
| Bachelor's degree | 2.49 | 2.50 |
| More than bachelor's (master's for CPS) | 1.89 | 2.20 |

*Unemployed for PSID here refers to if reported unemployed for at least 1 month

As for potential robustness concerns regarding the PSID's mortgage characteristics, Gerardi et al. (2018) performed various robustness checks on the PSID data set in their work.[7] They demonstrated that the mortgage characteristics in the PSID behaved very similar to data observed in the National American Housing Survey (AHS). The similarities were observed for median principal remaining, monthly mortgage payments, interest rates, terms, LTV ratios, second mortgages, and ARMs.

As noted by Gerardi et al. (2018), default rates in the PSID tend to be lower than the national averages reported elsewhere, such as in the National Delinquency Survey conducted by the Mortgage Bankers Association. In a similar vein, the PSID default rates were lower than those reported by the Federal Reserve for single-family residential mortgages.

We now examine how mortgage characteristics in the PSID compare with additional sources. The previous work with the PSID did not yet have a chance to examine the 2017 data point, so we put special attention here and ensure the quality of the newest data point. The 30-year fixed rate average reported by the Board of Governors on the Federal Reserve Economic Data (FRED) online database[8] for 2017 was 3.99%, which is very similar to that of the PSID at 3.91%. The average mortgage debt in Q1 2017 per Experian was $192,847, and the average mortgage debt reported at origination in 2017 for the PSID was around $190,287. The median house value in the 2017 PSID was $210,000 compared with a Q2 2017 median sold value quoted by Zillow of $201,000.

[7] There are several research papers that establish the representativeness of the financial characteristics in the PSID by showing its similarities to the Survey of Consumer Finance (Bernstein et al. (2010), Pfeffer et al. (2016), and Cooper et al. (2019)).
[8] Freddie Mac, 30-Year Fixed Rate Mortgage Average in the United States [MORTGAGE30US], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MORTGAGE30US, 2017-12-28.

In this comparison, we see that the PSID values of mortgage characteristics as of the latest update are similar to those reported by other sources meant to reflect national statistics. We take these similarities as a good indicator of the representativeness of the PSID mortgage data.

**Appendix C: Trends in 2017 data**

We compare the trends observed in the newest release of the 2017 data point to the previous years. Overall, the trends observed support the prominent story of a continued recovery. Default rates and unemployment rates trended downward as income appreciated. Both individual and household income in real terms has been slowly rising year over year.

Table C1: Frequency of mortgages by year

| Year | % with mortgage | % with 2nd mortgage | Unemployment Rate | Mortgage Default Rate |
|---|---|---|---|---|
| 2005 | 49.3 | 7.8 | 5.1 | - |
| 2007 | 47.3 | 8.8 | 4.9 | - |
| 2009 | 45.1 | 8.3 | 10.0 | 4.0 |
| 2011 | 41.2 | 6.6 | 8.6 | 3.5 |
| 2013 | 38.0 | 4.8 | 6.9 | 2.9 |
| 2015 | 36.6 | 3.7 | 5.0 | 1.8 |
| 2017 | 37.4 | 3.1 | 4.1 | 0.9 |

Source: PSID.

We observe a year-over-year decline in number of mortgage holders, with 2017 reporting only around 80% of the observations seen in 2009. The number of newly reported mortgages also continued to drop off. The average balance outstanding as well as house value saw a noticeable rise from previous years. These trends are also found in the SCF, where 46.3% of all families held a mortgage or home equity loan in 2007, 41.5% in 2013, and 40% in 2016.

**Appendix D: Replication with Probit Estimation**

In Tables D1, D2, and D3, we replicate Tables 5, 6, and 7 presented in the main text, but use a Probit estimation, which is meant to better capture the dependent binary variables, unemployment, and default. There are some important differences in the results, but the main effects are maintained by this specification. The equations presented in Table D1 exhibit some better overall fit than the equations in Table 5, but the main effect of unemployment in default seems to be lower. The first stage estimation for unemployment in Table D2 gives us a similar message as the linear probability specification of Table 6. Finally, the second stage estimation presented in Table D3 for the Probit estimation does also provide us with lower effect of unemployment on defaults than the linear probability specification. However, this specification does show a higher effect for 2009 and for unemployed borrowers who are in financial distress, as captured by the high CLTV.

# Tables

Table 1. Household's head characteristics by mortgage holding status

| | Mortgage | | Non-mortgage* | |
|---|---|---|---|---|
| Variables | Mean | SD | Mean | SD |
| Socio-demographics | | | | |
| Age | 45.0 | 11.0 | 40.5 | 12.2 |
| Male (%) | 84.4 | 36.3 | 60.7 | 48.8 |
| Black (%) | 21.0 | 40.8 | 48.8 | 50.0 |
| Married (%) | 73.6 | 44.1 | 30.5 | 46.0 |
| Never Married (%) | 11.1 | 31.4 | 42.6 | 49.4 |
| Years of Schooling | 14.1 | 2.4 | 13.0 | 2.5 |
| Less than HS (%) | 7.5 | 26.4 | 20.2 | 40.2 |
| HS (%) | 24.5 | 43.0 | 30.7 | 46.1 |
| More than HS (%) | 26.8 | 44.3 | 27.8 | 44.8 |
| 4-year College (%) | 23.2 | 42.2 | 12.9 | 33.5 |
| More than College (%) | 17.9 | 38.4 | 8.5 | 27.9 |
| Financial Characteristics | | | | |
| Household Head Income ($) | 65,927 | 95,342 | 28,516 | 50,098 |
| Total Family Income ($) | 112,329 | 117,941 | 49,484 | 66,513 |
| Household Income 0-50K (%) | 17.5 | 38.0 | 64.7 | 47.8 |
| Household Income 50-100K (%) | 38.9 | 48.8 | 25.1 | 43.4 |
| Household Income >=100K (%) | 43.6 | 49.6 | 10.2 | 30.2 |
| Has Liquid Assets (%) | 78.3 | 41.2 | 58.3 | 49.3 |
| Has Savings (%) | 85.6 | 35.1 | 54.6 | 50.9 |
| Has Retirement Account (%) | 32.5 | 46.8 | 11.2 | 31.6 |

Source: PSID.

*includes homeowners and non-homeowners

Table 2. Mortgage Characteristics

| | At origination | | Current values | |
|---|---|---|---|---|
| Variables | Mean | SD | Mean | SD |
| Years Remaining | 24.5 | 7.8 | 19.9 | 8.8 |
| House Value ($) | 274,653 | 247,224 | 245,372 | 233,586 |
| Principal Remaining ($) | 184,160 | 132,961 | 148,331 | 121,659 |
| Principal Remaining [2nd Mort] ($) | 29,949 | 47,258 | 18,578 | 39,432 |
| LTV ratio (%) | 73.4 | 23.7 | 65.9 | 30.0 |
| CLTV ratio (%) | 74.8 | 24.0 | 68.0 | 30.7 |
| Mortgage Interest Rate (%) | 4.63 | 1.94 | 4.68 | 1.85 |
| Mortgage Payment ($) | 1340 | 989 | 1223 | 924 |

Source: PSID.

Table 3: Default Rate by Employment Status and Unemployment Rate, in percent

| | Default Rate | | | Unemployment |
|---|---|---|---|---|
| Variables | All | Employed | Unemployed | Rate |
| Total | 2.66 | 2.35 | 8.54 | 4.96 |
| Marital Status | | | | |
| Married | 1.90 | 1.75 | 5.40 | 4.31 |
| Unwed | 3.67 | 3.05 | 13.10 | 6.17 |
| Widowed | 6.45 | 6.40 | 7.14 | 6.45 |
| Divorced | 4.75 | 3.96 | 15.00 | 7.08 |
| Separated | 9.43 | 8.56 | 18.18 | 9.02 |
| Race | | | | |
| Non-White | 5.39 | 4.97 | 11.21 | 6.70 |
| White | 1.70 | 1.45 | 7.09 | 4.35 |
| Sex | | | | |
| Male | 2.01 | 1.84 | 5.38 | 4.66 |
| Female | 6.17 | 5.15 | 20.63 | 6.59 |
| Generation | | | | |
| Boomer | 2.52 | 2.32 | 5.80 | 5.78 |
| X | 3.23 | 2.84 | 12.22 | 4.18 |
| Millennial | 1.42 | 1.05 | 8.42 | 4.99 |
| Education | | | | |
| Less than High School | 4.98 | 4.25 | 12.99 | 8.33 |
| High School | 3.70 | 3.31 | 10.43 | 5.43 |
| More than High School | 3.09 | 2.90 | 6.63 | 5.03 |
| 4-year College | 1.55 | 1.32 | 6.35 | 4.43 |
| More than College | 1.05 | 0.80 | 7.79 | 3.50 |
| Annual Household Income | | | | |
| 0-50K | 7.26 | 6.07 | 16.02 | 12.00 |
| 50-100K | 2.57 | 2.47 | 4.88 | 4.28 |
| >100K | 0.90 | 0.90 | 0.68 | 2.77 |

Source: PSID.

Table 4: Default Rate by Liquidity Source, in percent

| Liquidity Source | Liquid Assets | | Savings | | IRA | |
|---|---|---|---|---|---|---|
| | Yes | No | Yes | No | Yes | No |
| | 1.11 | 8.19 | 1.83 | 7.51 | 0.48 | 3.7 |

Source: PSID.

Table 5: Default in percent, OLS Estimation

| | Unemployment Variable Level. Comparable 1% variation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | State | | County | | Individual | | | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Unemployed** | | | | | $0.04^{c}$ | $0.03^{c}$ | $0.04^{c}$ | $0.03^{c}$ |
| **Unemployed in 2009** | | | | | | $0.02^{a}$ | | $0.03^{b}$ |
| **Unemployed in 2009 with CLTV>100%** | | | | | | $0.08^{b}$ | | $0.08^{b}$ |
| **Unemployment Rate** | $0.16^{b}$ | | $0.10^{b}$ | | | | | |
| **Change in Unemployment Rate** | | 0.12 | | $0.22^{b}$ | | | | |
| **% Change in State HPI** | $-7.39^{b}$ | $-9.77^{c}$ | | | $-11.37^{c}$ | $-10.56^{c}$ | | |
| **% Change in County HPI** | | | -1.36 | -0.54 | | | $-3.43^{a}$ | -2.83 |
| **CLTV Bucket (Base:0-50%)** | | | | | | | | |
| CLTV(50-90%) | $0.70^{b}$ | $0.71^{b}$ | $0.71^{b}$ | $0.72^{b}$ | $0.74^{b}$ | $0.73^{b}$ | $0.75^{b}$ | $0.74^{b}$ |
| CLTV(90-100%) | $0.99^{b}$ | $1.07^{b}$ | $1.06^{b}$ | $1.11^{b}$ | $1.15^{b}$ | $1.14^{b}$ | $1.19^{c}$ | $1.18^{c}$ |
| CLTV(>100%) | $7.18^{c}$ | $7.35^{c}$ | $7.36^{c}$ | $7.43^{c}$ | $7.38^{c}$ | $7.26^{c}$ | $7.43^{c}$ | $7.31^{c}$ |
| **DTI (Base:<15%)** | | | | | | | | |
| DTI(15-30%) | $0.53^{b}$ | $0.57^{b}$ | $0.56^{b}$ | $0.57^{b}$ | $0.46^{a}$ | $0.48^{a}$ | $0.48^{a}$ | $0.50^{a}$ |
| DTI(30-45%) | $5.51^{c}$ | $5.55^{c}$ | $5.60^{c}$ | $5.61^{c}$ | $5.36^{c}$ | $5.40^{c}$ | $5.43^{c}$ | $5.46^{c}$ |
| DTI(>45%) | $9.14^{c}$ | $9.18^{c}$ | $9.21^{c}$ | $9.24^{c}$ | $8.63^{c}$ | $8.61^{c}$ | $8.68^{c}$ | $8.66^{c}$ |
| **Has Liquid Assets** | $-4.64^{c}$ | $-4.69^{c}$ | $-4.72^{c}$ | $-4.75^{c}$ | $-4.59^{c}$ | $-4.58^{c}$ | $-4.65^{c}$ | $-4.63^{c}$ |
| **Has Savings** | -0.19 | -0.15 | -0.08 | -0.08 | -0.11 | -0.12 | -0.02 | -0.03 |
| **Has IRA** | $-0.96^{c}$ | $-0.94^{c}$ | $-0.96^{c}$ | $-0.94^{c}$ | $-0.97^{c}$ | $-0.98^{c}$ | $-0.98^{c}$ | $-0.99^{c}$ |
| **Variable Rate** | $2.14^{c}$ | $2.16^{c}$ | $2.19^{c}$ | $2.19^{c}$ | $2.16^{c}$ | $2.14^{c}$ | $2.20^{c}$ | $2.18^{c}$ |
| **At Least College** | -0.44 | -0.44 | -0.46 | -0.46 | -0.40 | -0.41 | -0.42 | -0.43 |
| **Marital Status (Base:Married)** | | | | | | | | |
| Marital Status(Unwed) | 0.48 | 0.46 | 0.44 | 0.42 | 0.52 | 0.51 | 0.48 | 0.47 |
| Marital Status(Was married) | 0.58 | 0.55 | 0.52 | 0.51 | 0.53 | 0.54 | 0.48 | 0.49 |
| **White** | $-1.24^{c}$ | $-1.28^{c}$ | $-1.28^{c}$ | $-1.28^{c}$ | $-1.24^{c}$ | $-1.24^{c}$ | $-1.24^{c}$ | $-1.25^{c}$ |
| **Female** | $1.56^{c}$ | $1.54^{c}$ | $1.58^{c}$ | $1.55^{c}$ | $1.61^{c}$ | $1.58^{c}$ | $1.63^{c}$ | $1.60^{c}$ |
| **Generation (Base: Baby Boomer)** | | | | | | | | |
| Generation (X) | $0.81^{c}$ | $0.75^{b}$ | $0.72^{b}$ | $0.71^{b}$ | $0.78^{c}$ | $0.77^{c}$ | $0.73^{b}$ | $0.73^{b}$ |
| Generation (Y) | -0.47 | $-0.65^{a}$ | $-0.74^{a}$ | $-0.78^{b}$ | $-0.67^{a}$ | $-0.70^{a}$ | $-0.83^{b}$ | $-0.85^{b}$ |
| **Constant** | 0.23 | 1.44 | 0.47 | 1.22 | 1.03 | 1.08 | 0.78 | 0.86 |
| Nobs | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 |
| Ad. R2 | 0.0748 | 0.0746 | 0.0736 | 0.0737 | 0.0774 | 0.0778 | 0.0763 | 0.0769 |

Note. a: p<.1, b: p<.05, c: p<.01.

Table 6: Individual Unemployment Estimation

| | No U Comp. | | U Comp. | | Gyourko-Tracy | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| State Unemployment Rate | | | | | 0.45 $^{c}$ | |
| County Unemployment Rate | | | | | | 0.21 $^{c}$ |
| Unemployment Compensation | | | 45.96 $^{c}$ | 45.86 $^{c}$ | | |
| Welfare | 18.03 $^{c}$ | 18.10 $^{c}$ | 17.61 $^{c}$ | 17.53 $^{c}$ | | |
| **Year (Base:2009)** | | | | | | |
| Year (2011) | | 1.77 $^{c}$ | | 1.05 $^{b}$ | | |
| Year (2013) | | -0.02 | | 0.79 $^{a}$ | | |
| Year (2015) | | -0.33 | | 0.73 $^{a}$ | | |
| Year (2017) | | -1.81 $^{c}$ | | -0.29 | | |
| **At Least College** | -1.28 $^{c}$ | -1.19 $^{c}$ | -0.31 | -0.29 | | |
| **Marital Status (Base:Married)** | | | | | | |
| Marital Status(Unwed) | 1.58 $^{b}$ | 1.46 $^{b}$ | 0.82 | 0.79 | | |
| Marital Status(Was married) | 2.17 $^{c}$ | 2.17 $^{c}$ | 1.74 $^{c}$ | 1.74 $^{c}$ | | |
| **White** | -1.41 $^{c}$ | -1.46 $^{c}$ | -1.24 $^{c}$ | -1.25 $^{c}$ | | |
| **Female** | -1.72 $^{b}$ | -1.62 $^{b}$ | -1.09 $^{a}$ | -1.05 $^{a}$ | | |
| **Generation (Base: Baby Boomer)** | | | | | | |
| Generation (X) | -1.34 $^{c}$ | -1.17 $^{c}$ | -0.55 $^{a}$ | -0.52 $^{a}$ | | |
| Generation (Y) | -0.72 | -0.13 | 0.28 | 0.39 | | |
| **DTI (Base:<15%)** | | | | | | |
| DTI(15-30%) | 2.61 $^{c}$ | 2.44 $^{c}$ | 1.95 $^{c}$ | 1.92 $^{c}$ | | |
| DTI(30-45%) | 5.16 $^{c}$ | 4.87 $^{c}$ | 3.47 $^{c}$ | 3.43 $^{c}$ | | |
| DTI(>45%) | 14.18 $^{c}$ | 13.87 $^{c}$ | 12.45 $^{c}$ | 12.39 $^{c}$ | | |
| **Constant** | 6.74 $^{c}$ | 6.61 $^{c}$ | 3.76 $^{c}$ | 3.26 $^{c}$ | 1.82 $^{c}$ | 3.51 $^{c}$ |
| Nobs | 12268 | 12268 | 12268 | 12268 | 12268 | 12268 |
| Ad. R2 | 0.021 | 0.023 | 0.204 | 0.204 | 0.003 | 0.001 |

Note. a: p<.1, b: p<.05, c: p<.01.

Table 7: Default in percent, IV Estimation. Effect of a 1% increase in the unemployment rate

| | First Stage Estimation | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | No Unemp. Compensation | | | | Unemp. Compensation | | | | Gyourko-Tracy | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Unemployed** | 0.26 $^{c}$ | 0.36 $^{c}$ | 0.35 $^{c}$ | 0.45 $^{c}$ | 0.03 $^{b}$ | 0.02 | 0.03 $^{b}$ | 0.01 | 0.34 $^{b}$ | 0.48 $^{b}$ |
| **Unemployed in 2009** | | 0.13 $^{b}$ | | 0.21 $^{c}$ | | 0.02 | | 0.04 | | |
| **Unemployed in 2009 with CLTV>100%** | | 0.79 $^{c}$ | | 0.79 $^{c}$ | | 0.37 $^{c}$ | | 0.37 $^{c}$ | | |
| **% Change in State HPI** | -9.43 $^{c}$ | -3.57 | | | -11.51 $^{c}$ | -9.95 $^{c}$ | | | -7.39 $^{b}$ | |
| **% Change in County HPI** | | | -1.40 | 4.30 $^{a}$ | | | -3.50 $^{a}$ | -2.16 | | -1.36 |
| **CLTV Bucket (Base:0-50%)** | | | | | | | | | | |
| CLTV(50-90%) | 0.71 $^{b}$ | 0.70 $^{b}$ | 0.71 $^{b}$ | 0.70 $^{b}$ | 0.72 $^{b}$ | 0.72 $^{b}$ | 0.73 $^{b}$ | 0.73 $^{b}$ | 0.70 $^{c}$ | 0.71 $^{c}$ |
| CLTV(90-100%) | 0.99 $^{b}$ | 0.96 $^{b}$ | 1.01 $^{b}$ | 0.94 $^{b}$ | 1.08 $^{b}$ | 1.09 $^{b}$ | 1.13 $^{b}$ | 1.13 $^{b}$ | 0.99 $^{b}$ | 1.06 $^{b}$ |
| CLTV(>100%) | 7.24 $^{c}$ | 6.09 $^{c}$ | 7.27 $^{c}$ | 6.11 $^{c}$ | 7.36 $^{c}$ | 6.82 $^{c}$ | 7.42 $^{c}$ | 6.87 $^{c}$ | 7.18 $^{c}$ | 7.36 $^{c}$ |
| **DTI (Base:<15%)** | | | | | | | | | | |
| DTI(15-30%) | -0.10 | -0.44 | -0.30 | -0.69 $^{b}$ | 0.49 $^{a}$ | 0.52 $^{b}$ | 0.50 $^{a}$ | 0.54 $^{b}$ | 0.53 $^{b}$ | 0.56 $^{b}$ |
| DTI(30-45%) | 4.23 $^{c}$ | 3.30 $^{c}$ | 3.85 $^{c}$ | 2.77 $^{c}$ | 5.40 $^{c}$ | 5.36 $^{c}$ | 5.46 $^{c}$ | 5.42 $^{c}$ | 5.51 $^{c}$ | 5.60 $^{c}$ |
| DTI(>45%) | 5.45 $^{c}$ | 3.12 $^{b}$ | 4.27 $^{c}$ | 1.59 | 8.73 $^{c}$ | 8.60 $^{c}$ | 8.77 $^{c}$ | 8.64 $^{c}$ | 9.14 $^{c}$ | 9.21 $^{c}$ |
| **Has Liquid Assets** | -4.63 $^{c}$ | -4.58 $^{c}$ | -4.66 $^{c}$ | -4.59 $^{c}$ | -4.65 $^{c}$ | -4.64 $^{c}$ | -4.71 $^{c}$ | -4.69 $^{c}$ | -4.64 $^{c}$ | -4.72 $^{c}$ |
| **Has Savings** | -0.14 | -0.24 | -0.06 | -0.24 | -0.13 | -0.14 | -0.03 | -0.07 | -0.19 | -0.08 |
| **Has IRA** | -0.96 $^{c}$ | -0.96 $^{c}$ | -0.98 $^{c}$ | -0.96 $^{c}$ | -0.95 $^{c}$ | -0.93 $^{c}$ | -0.96 $^{c}$ | -0.94 $^{c}$ | -0.96 $^{c}$ | -0.96 $^{c}$ |
| **Variable Rate** | 2.18 $^{c}$ | 2.12 $^{c}$ | 2.22 $^{c}$ | 2.14 $^{c}$ | 2.15 $^{c}$ | 2.14 $^{c}$ | 2.20 $^{c}$ | 2.17 $^{c}$ | 2.14 $^{c}$ | 2.19 $^{c}$ |
| **At Least College** | -0.12 | 0.05 | -0.03 | 0.16 | -0.41 | -0.42 | -0.42 | -0.44 | -0.44 $^{b}$ | -0.46 $^{b}$ |
| **Marital Status (Base:Married)** | | | | | | | | | | |
| Marital Status(Unwed) | -0.87 $^{a}$ | -1.06 $^{b}$ | 0.97 $^{b}$ | 1.19 $^{b}$ | -0.51 | -0.50 | 0.47 | 0.46 | -0.48 | 0.44 |
| Marital Status(Was married) | -0.48 | -0.74 | 0.29 | 0.22 | 0.03 | 0.06 | 0.49 | 0.51 | 0.10 | 0.52 |
| **White** | -0.92 $^{c}$ | -0.75 $^{b}$ | -0.81 $^{b}$ | -0.60 $^{a}$ | -1.24 $^{c}$ | -1.26 $^{c}$ | -1.24 $^{c}$ | -1.27 $^{c}$ | -1.24 $^{c}$ | -1.28 $^{c}$ |
| **Female** | 1.98 $^{c}$ | 2.21 $^{c}$ | 2.14 $^{c}$ | 2.38 $^{c}$ | 1.59 $^{c}$ | 1.56 $^{c}$ | 1.62 $^{c}$ | 1.57 $^{c}$ | 1.56 $^{b}$ | 1.58 $^{c}$ |
| **Generation (Base: Baby Boomer)** | | | | | | | | | | |
| Generation (X) | 1.09 $^{c}$ | 1.27 $^{c}$ | 1.16 $^{c}$ | 1.38 $^{c}$ | 0.78 $^{c}$ | 0.76 $^{c}$ | 0.73 $^{b}$ | 0.72 $^{b}$ | 0.81 $^{b}$ | 0.72 $^{b}$ |
| Generation (Y) | -0.51 | -0.41 | -0.61 $^{a}$ | -0.43 | -0.66 $^{a}$ | -0.67 $^{a}$ | -0.82 $^{b}$ | -0.82 $^{b}$ | -0.47 | -0.74 $^{b}$ |
| **Constant** | 0.07 | -0.81 | -1.76 | -2.91 $^{b}$ | 1.67 $^{b}$ | 1.76 $^{b}$ | 0.91 | 1.05 | 0.08 | -1.20 |
| Nobs | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 |
| Ad. R2 | 0.0750 | 0.0774 | 0.0742 | 0.0775 | 0.0748 | 0.0767 | 0.0737 | 0.0758 | 0.0748 | 0.0736 |

Note. a: p<.1, b: p<.05, c: p<.01.

Table D1: Probit Estimation for Default. Marginal Effects in percent. Effect of a 1% increase in the Unemployment Rate

| | Unemployment Variable Level | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | State | | County | | Individual | | | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Unemployed** | | | | | 0.02 c | 0.02 c | 0.02 c | 0.02 c |
| **Unemployed in 2009** | | | | | | 0.01 | | 0.01 |
| **Unemployed in 2009 with CLTV>100%** | | | | | | -0.01 | | 0.00 |
| **Unemployment Rate** | 0.17 c | | 0.10 b | | | | | |
| **Change in Unemployment Rate** | | 0.06 | | 0.20 b | | | | |
| **% Change in State HPI** | -4.65 a | -8.77 c | | | -9.54 c | -9.27 c | | |
| **% Change in County HPI** | | | -0.57 | -0.14 | | | -2.88 | -2.50 |
| **CLTV Bucket (Base:0-50%)** | | | | | | | | |
| CLTV(50-90%) | 0.83 c | 0.83 c | 0.82 c | 0.83 c | 0.84 c | 0.83 c | 0.84 c | 0.83 c |
| CLTV(90-100%)+R121 | 1.20 c | 1.25 c | 1.24 c | 1.27 c | 1.32 c | 1.31 c | 1.35 c | 1.34 c |
| CLTV(>100%) | 4.91 c | 5.23 c | 5.23 c | 5.34 c | 5.30 c | 5.32 c | 5.38 c | 5.39 c |
| **DTI (Base:<15%)** | | | | | | | | |
| DTI(15-30%) | 0.86 c | 0.89 c | 0.90 c | 0.90 c | 0.83 c | 0.83 c | 0.86 c | 0.86 c |
| DTI(30-45%) | 3.55 c | 3.62 c | 3.71 c | 3.72 c | 3.46 c | 3.46 c | 3.60 c | 3.60 c |
| DTI(>45%) | 5.46 c | 5.55 c | 5.62 c | 5.68 c | 4.81 c | 4.83 c | 4.94 c | 4.96 c |
| **Has Liquid Assets** | -3.07 c | -3.10 c | -3.13 c | -3.13 c | -2.99 c | -2.98 c | -3.02 c | -3.02 c |
| **Has Savings** | -0.01 | 0.01 | 0.06 | 0.04 | 0.03 | 0.03 | 0.11 | 0.10 |
| **Has IRA** | -2.38 c | -2.35 c | -2.37 c | -2.32 c | -2.34 c | -2.35 c | -2.31 c | -2.32 c |
| **Variable Rate** | 1.29 c | 1.32 c | 1.37 c | 1.36 c | 1.35 c | 1.34 c | 1.43 c | 1.41 c |
| **At Least College** | -0.78 a | -0.77 a | -0.81 b | -0.79 a | -0.81 b | -0.81 b | -0.82 b | -0.82 b |
| **Marital Status (Base:Married)** | | | | | | | | |
| Marital Status(Unwed) | 0.02 | 0.03 | 0.00 | -0.02 | 0.08 | 0.07 | 0.04 | 0.03 |
| Marital Status(Was married) | 0.30 | 0.28 | 0.23 | 0.23 | 0.27 | 0.27 | 0.22 | 0.22 |
| **White** | -0.89 c | -0.95 c | -0.95 c | -0.96 c | -0.95 c | -0.94 c | -0.96 c | -0.96 c |
| **Female** | 0.79 b | 0.78 b | 0.81 b | 0.79 b | 0.82 b | 0.81 b | 0.84 b | 0.83 b |
| **Generation (Base: Baby Boomer)** | | | | | | | | |
| Generation (X) | 0.84 c | 0.79 c | 0.78 c | 0.80 c | 0.78 c | 0.78 c | 0.76 c | 0.76 c |
| Generation (Y) | -0.48 | -0.61 a | -0.66 b | -0.67 b | -0.70 b | -0.69 b | -0.78 b | -0.78 b |
| Nobs | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 |
| Pseudo R2 | 0.2373 | 0.2353 | 0.2323 | 0.2324 | 0.2420 | 0.2422 | 0.2378 | 0.2382 |

Note. a: p<.1, b: p<.05, c:  p<.01.

Table D2: Probit Estimation for First Stage Individual Employment

| Variables | No U Comp. (1) | No U Comp. (2) | U Comp. (3) | U Comp. (4) |
|---|---|---|---|---|
| Unemployment Compensation | | | 14.63 c | 14.54 c |
| Welfare | 8.12 c | 8.12 c | 7.53 c | 7.47 c |
| **Year (Base:2009)** | | | | |
| Year (2011) | | 1.61 c | | 0.63 |
| Year (2013) | | -0.07 | | 0.57 |
| Year (2015) | | -0.46 | | 0.64 |
| Year (2017) | | -1.94 c | | -0.58 |
| **At Least College** | -1.52 c | -1.41 c | -0.66 a | -0.63 a |
| **Marital Status (Base:Married)** | | | | |
| Marital Status(Unwed) | 1.43 b | 1.32 b | 0.84 a | 0.82 a |
| Marital Status(Was married) | 2.01 c | 1.98 c | 1.53 b | 1.50 b |
| **White** | -1.31 c | -1.36 c | -1.17 c | -1.18 c |
| **Female** | -1.45 b | -1.36 b | -0.86 a | -0.83 a |
| **Generation (Base: Baby Boomer)** | | | | |
| Generation (X) | -1.39 c | -1.22 c | -0.62 b | -0.60 a |
| Generation (Y) | -0.74 | -0.10 | 0.34 | 0.49 |
| **DTI (Base:<15%)** | | | | |
| DTI(15-30%) | 2.63 c | 2.47 c | 1.92 c | 1.89 c |
| DTI(30-45%) | 4.95 c | 4.56 c | 3.28 c | 3.19 c |
| DTI(>45%) | 13.21 c | 12.64 c | 11.17 c | 11.05 c |
| Nobs | 12268 | 12268 | 12268 | 12268 |
| Pseudo R2 | 0.043 | 0.050 | 0.237 | 0.239 |

Note. a: p<.1, b: p<.05, c: p<.01.

Table D3: Second Stage Probit for Default, Marginal Effects in percent. Effect of a 1% increase in the Unemployment Rate

| | First Stage Estimation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No Unemp. Compensation | | | | Unemp. Compensation | | | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Unemployed** | 0.11 [b] | 0.12 [b] | 0.13 [c] | 0.15 [c] | 0.02 [b] | 0.01 | 0.02 [b] | 0.01 |
| **Unemployed in 2009** | | 0.04 | | 0.09 [b] | | 0.01 | | 0.02 |
| **Unemployed in 2009 with CLTV>100%** | | 0.03 | | 0.04 | | 0.00 | | 0.00 |
| **% Change in State HPI** | -8.89 [c] | -7.08 [c] | | | -9.56 [c] | -9.15 [c] | | |
| **% Change in County HPI** | | | -2.39 | 0.38 | | | -2.97 | -2.26 |
| **CLTV Bucket (Base:0-50%)** | | | | | | | | |
| CLTV(50-90%) | 0.84 [c] | 0.84 [c] | 0.84 [c] | 0.84 [c] | 0.83 [c] | 0.84 [c] | 0.84 [c] | 0.84 [c] |
| CLTV(90-100%) | 1.23 [c] | 1.21 [c] | 1.25 [c] | 1.22 [c] | 1.27 [c] | 1.27 [c] | 1.30 [c] | 1.30 [c] |
| CLTV(>100%) | 5.15 [c] | 5.02 [c] | 5.19 [c] | 5.03 [c] | 5.25 [c] | 5.24 [c] | 5.32 [c] | 5.31 [c] |
| **DTI (Base:<15%)** | | | | | | | | |
| DTI(15-30%) | 0.67 [b] | 0.62 [b] | 0.65 [b] | 0.56 [b] | 0.85 [c] | 0.85 [c] | 0.88 [c] | 0.88 [c] |
| DTI(30-45%) | 2.86 [c] | 2.68 [c] | 2.81 [c] | 2.49 [c] | 3.50 [c] | 3.50 [c] | 3.63 [c] | 3.64 [c] |
| DTI(>45%) | 2.64 [b] | 2.13 [a] | 2.18 [a] | 1.37 | 4.99 [c] | 5.00 [c] | 5.09 [c] | 5.11 [c] |
| **Has Liquid Assets** | -3.10 [c] | -3.09 [c] | -3.13 [c] | -3.11 [c] | -3.07 [c] | -3.06 [c] | -3.10 [c] | -3.10 [c] |
| **Has Savings** | 0.06 | 0.03 | 0.14 | 0.06 | 0.03 | 0.02 | 0.11 | 0.08 |
| **Has IRA** | -2.37 [c] | -2.36 [c] | -2.35 [c] | -2.34 [c] | -2.36 [c] | -2.36 [c] | -2.33 [c] | -2.33 [c] |
| **Variable Rate** | 1.36 [c] | 1.34 [c] | 1.43 [c] | 1.38 [c] | 1.33 [c] | 1.32 [c] | 1.41 [c] | 1.39 [c] |
| **At Least College** | -0.61 | -0.57 | -0.59 | -0.53 | -0.78 [a] | -0.78 [a] | -0.80 [a] | -0.80 [b] |
| **Marital Status (Base:Married)** | | | | | | | | |
| Marital Status(Unwed) | 0.22 | 0.25 | 0.23 | 0.28 | 0.05 | 0.04 | 0.01 | 0.00 |
| Marital Status(Was married) | 0.15 | 0.13 | 0.07 | 0.05 | 0.27 | 0.27 | 0.21 | 0.22 |
| **White** | -0.76 [c] | -0.72 [b] | -0.73 [c] | -0.65 [b] | -0.93 [c] | -0.93 [c] | -0.94 [c] | -0.95 [c] |
| **Female** | 1.00 [b] | 1.04 [b] | 1.07 [b] | 1.12 [c] | 0.80 [b] | 0.79 [b] | 0.82 [b] | 0.80 [b] |
| **Generation (Base: Baby Boomer)** | | | | | | | | |
| Generation (X) | 0.98 [c] | 1.04 [c] | 1.02 [c] | 1.11 [c] | 0.81 [c] | 0.81 [c] | 0.80 [c] | 0.80 [c] |
| Generation (Y) | -0.55 [a] | -0.51 [a] | -0.61 [b] | -0.53 [a] | -0.62 [a] | -0.61 [a] | -0.71 [b] | -0.69 [b] |
| Nobs | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 | 12,268 |
| Pseudo R2 | 0.2364 | 0.2369 | 0.2329 | 0.2350 | 0.2362 | 0.2363 | 0.2320 | 0.2326 |

Note. a: p<.1, b: p<.05, c: p<.01.