NBER WORKING PAPER SERIES

CAN'T PAY OR WON'T PAY? UNEMPLOYMENT, NEGATIVE EQUITY, AND STRATEGIC DEFAULT

Kristopher Gerardi
Kyle F. Herkenhoff
Lee E. Ohanian
Paul S. Willen

Working Paper 21630
http://www.nber.org/papers/w21630

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2015

We thank Gene Amromin, Jan Brueckner, Satyajit Chatterjee, Morris Davis, Andra Ghent, John Krainer, Ed Kung, Stuart Gabriiel, Erwan Quintin, Joe Tracy, and Rob Valetta, and seminar participants for helpful comments. The views expressed in this article are those of the authors, and not those of the Federal Reserve Banks of Atlanta, Boston, Minneapolis, the Federal Reserve System, or the National Bureau of Economic Research.

Can't Pay or Won't Pay? Unemployment, Negative Equity, and Strategic Default
Kristopher Gerardi, Kyle F. Herkenhoff, Lee E. Ohanian, and Paul S. Willen
NBER Working Paper No. 21630
October 2015
JEL No. G21,G33,R3,R51

ABSTRACT

Previous research on mortgage default has been constrained by data limitations, including lack of data on mortgagor employment status. This paper studies mortgage default using PSID data, which includes a richer set of covariates, including employment status, equity, and other assets. In sharp contrast to prior studies, we find that unemployment and other negative financial shocks are key default predictors. Using wealth data, we find a limited scope for strategic default, as only 1/3 of underwater defaulters have enough assets to pay their mortgage. We discuss the implications of these findings for theoretical default models and for loss mitigation policies

Kristopher Gerardi
Federal Reserve Bank of Atlanta
1000 Peachtree St. NE
Atlanta, GA 30309
kristopher.gerardi@atl.frb.org

Kyle F. Herkenhoff
Department of Economics
University of Minnesota
kfh@umn.edu

Lee E. Ohanian
8283 Bunche Hall
UCLA, Department of Economics
Box 951477
Los Angeles, CA 90095
and NBER
ohanian@econ.ucla.edu

Paul S. Willen
Federal Reserve Bank of Boston
600 Atlantic Avenue
Boston, MA 02210-2204
and NBER
willen968@gmail.com

1. Introduction

This paper studies the contribution of household-level employment, income, and expense shocks to mortgage default decisions. We exploit new data from the Panel Study of Income Dynamics (PSID) to provide the most systematic and detailed analysis of these factors in the literature.[1] These are the first data to combine a household's mortgage payment/default status with data on the household's employment status, income, assets, marital status, medical expenses, and other socioeconomic factors. These data therefore allow us to analyze directly the impact of household-level employment and financial variables on mortgage default decisions, unlike previous studies that relied on crude proxies for household-level financial variables, such as using regional unemployment rates as a proxy for individual household employment status.

These new data provide very different answers regarding the importance of employment and financial factors for understanding mortgage default. We find that over 30 percent of defaulting households experienced an employment loss before their default, and that 80 percent experienced a major shock to their cash flow, including job loss, a severe income loss, divorce, or hospitalization. In contrast, only about 40 percent of defaulters believed they had negative equity. Using standard regression analysis that controls for a number of factors, we find that job loss by the head of household has an impact on the decision to default that is equivalent to a 56 percent reduction in home equity. The impact of spousal job loss is equivalent to a 43 percent reduction in equity. These findings stand in sharp contrast to the findings of previous studies that are based on regional proxies for employment and financial status and concluded that unemployment was of only limited importance (see Gyourko and Tracy (2014)'s discussion of the topic).

[1] Early empirical work on mortgage default includes Campbell and Dietrich (1983), Foster and Order (1985), Vandell (1995), Deng et al. (1996), Deng, Quigley, and Order (2000), Böheim and Taylor (2000), among others. Recent work on empirical mortgage default includes Foote, Gerardi, and Willen (2008), Haughwout, Peach, and Tracy (2008), Mayer, Pence, and Sherlund (2009), Gathergood (2009), Goodman et al. (2010), Elul et al. (2010), Bhutta, Dokko, and Shan (2011), and Mocetti and Viviano (2013), among others.

We also study how shocks to employment, income, and expenses matter for default decisions. We use the PSID to construct implicit estimates of the defaulters' budget constraints, and divide defaulters into two groups: those that are able to pay, but don't, (often referred to as *strategic defaulters*), and those that are unable to pay. We find very few strategic defaulters within the PSID. Fewer than 1 percent of the "can pay" households (those with a head (and/or spouse) who is employed and that have net liquid asset holdings equivalent to at least six months of mortgage payments) default. In sharp contrast, we find that many homeowners who are reasonably classified as unable to pay, whom we term "can't pay" households, continue to pay their mortgage. Specifically, 81 percent of the "can't pay" households—those with a head (and/or spouse) who is unemployed, and that have net liquid assets that are less than one monthly mortgage payment—are current on their mortgage. Even two-thirds of those that (i) are unable to pay according to this definition and (ii) also have negative equity in their homes, are current on their mortgages. Our findings have key implications for widely used theoretical models of mortgage default. The significance of household-level financial shocks indicates that frictionless, option-value-theoretic models, such as Kau and Keenan (1995) and Vandell (1995), are at odds with these data. Moreover, the fact that many households that experience *double trigger events*—becoming unemployed or receiving other major negative financial shocks, and that also have negative equity—do pay their mortgage suggests that the popular "double trigger" model of default is at odds with these data.

Our findings suggest that classes of models that feature borrowing constraints and heterogeneity in terms of how income, assets, and equity interact, such as Corbae and Quintin (2009), Garriga and Schlagenhauf (2009), Chatterjee and Eyigungor (2011), Campbell and Cocco (2011), Hedlund (2011), Schelkle (2011), and Laufer (2012), may be consistent with these data. More broadly, however, any model of optimal mortgage default will require features that dampen the incentive for mortgagors to default, in order to match the very high fraction of homeowners who are severely financially distressed and who also remain current on their mortgage.

Our findings also have key implications for economic policy. We argue that low default rates among “can’t pay” borrowers may significantly complicate loss mitigation policies. We show that the size of a payment or principal reduction that a lender is willing to offer to a distressed homeowner is increasing in the probability of that borrower defaulting. Thus, low default probabilities among distressed borrowers reduce the ability of the lender to mitigate foreclosures.

The remainder of the paper is structured as follows: Section 2 describes the PSID data and discusses the representativeness of the sample. Section 3 summarizes the types of shocks that characterize defaulters and describes the baseline results. Section 4 measures the incidence, income, and wealth of “can’t pay” and “won’t pay” households and, in doing so, provides several direct measures of strategic default. Section 5 describes the relation of our findings to existing models of mortgage default and discusses the implications of our results for loss mitigation policies. Finally, Section 6 concludes.

2. PSID Data

The primary data used in this study come from the 2009 and 2011 PSID Supplements on Housing, Mortgage Distress, and Wealth Data. We restrict the sample to mortgagor heads who report being in the labor force and who are between the ages of 24 and 65. We also restrict our sample to households with loan to value ratios below 250 percent that had not defaulted as of a prior survey.[2] This leaves us with 5,281 households.

In the remainder of this section we discuss the representativeness of the PSID data regarding housing and mortgage market variables and then present a detailed set of summary statistics for the sample of all households and the sample of households in default.

[2]The LTV requirement drops what appear to be misreported mortgage and home values (inclusion of these observations does not change our main results), and dropping defaulting households from future observations simply eliminates double counting.

2.1. Representativeness of PSID Sample

Table 1 compares mortgage statistics from our PSID sample with data from the 2011 National American Housing Survey (AHS).[3] In general, mortgage characteristics are quite similar across the two datasets. The median outstanding principal balance is identical and the median monthly mortgage payment is within $100. The median mortgage interest rates, remaining terms, and LTV ratios are also extremely close across the datasets. A slightly higher fraction of mortgagors report having a second mortgage (18 percent versus 13 percent) and an adjustable-rate mortgage (9 percent versus 7 percent) in the PSID than in the AHS.

Delinquency rates among mortgagors in the PSID are slightly lower than in other nationally representative datasets. According to the National Delinquency Survey conducted by the Mortgage Bankers Association (MBA), the average 60+ day delinquency rate in 2009 was 5.8 percent, whereas in the PSID it was approximately 4 percent.[4] Similarly, the 30+ day delinquency rate in 2009 according to the MBA was 9.4 percent compared with 6.5 percent in our PSID sample.[5]

Figure 1 displays the distribution of housing equity in our sample compared with the distribution in Corelogic.[6] According to Corelogic, slightly more than 10 percent of properties

[3]The AHS is conducted biennially by the U.S. Census Bureau. It has a sample size of about 47,000 housing units and was designed to provide representative data on the U.S. housing and mortgage markets.

[4]Throughout the paper, we do not weight the observations because default outcomes are not post-stratum in the PSID. The point is best made with an important example. As mentioned in the text, the MBA reports an average 60+ day delinquency rate in 2009 of 5.8 percent. In the 2009 PSID, the unweighted default rate among mortgagors is 3.86 percent. However, the default rate in the 2009 PSID, weighted using the family weights, is only 3.15 percent. The weights significantly lower the default rate compared to the unweighted default rate and yield a default rate roughly half the magnitude of the population default rate. A similar set of outcomes is also true in the Survey of Consumer Finances (SCF). The additional set of results with and without the weights is simply to demonstrate that the main asset distribution results are insensitive to the weights.

[5] The Board of Governors of the Federal Reserve System also publishes delinquency rates among FDIC insured banks, and they report an average 30+ day delinquency rate of 9.1 percent averaged over 2009.

[6]The bottom panel of Figure 1 comes from the August 13, 2009 report entitled "Summary of Second Quarter 2009 Negative Equity Data from First American CoreLogic" `http://www.loanperformance.com/infocenter/library/FACL%20Negative%20Equity_final_081309.pdf` Corelogic uses a national database of property transactions that covers 43 states to come up with their equity estimates, and thus their data should be quite representative of the U.S. population. Corelogic uses administrative data on outstanding mortgage balances and estimates of housing values to compute equity, while we use reported mortgage balances and housing values in the PSID.

had greater than 25 percent negative equity, while slightly less than 4 percent did so in the PSID. While there could be many reasons for the divergence in equity estimates between the two databases, households tend to over-report house values as compared to actual selling prices by 5 percent to 10 percent (see Benítez-Silva et al. (2008)). While the PSID understates the amount of negative equity in the economy relative to Corelogic estimates, we do not view this as a significant drawback of our analysis. To determine the dual roles that negative equity and unemployment play in causing mortgage delinquency and default, we believe that self-reported equity is the most appropriate equity measure. In choosing whether or not to default, households take into account their own perceived valuation of their home, which may or may not be derived in part from a third-party estimate (such as Corelogic or Zillow). To put it another way, the value of using self-reported equity values is that only those households that believe that they are in positions of negative equity are flagged as having negative equity, and this is the group of households that we expect to be most sensitive to negative equity in terms of default behavior.[7]

2.2. PSID Summary Statistics: All Households

In the next two sections, we compare defaulting and nondefaulting households along a number of dimensions that are new to the literature. We find that the two groups of households look quite different in terms of income, employment, and wealth. In this section, we focus on summary statistics for *all* households in our PSID sample. Below, in Section 2.3, we present a similar set of summary statistics for only the households that are delinquent on their mortgage payments.

Panel (A) of Table 2 displays demographic information. The average age of the household heads in our sample is approximately 44 years. About 85 percent of the household heads in our sample are male, 74 percent are white, and 21 percent are black. The majority

[7] In addition, it is likely the case that many households have information about the condition of their home and the state of their local housing market that is not captured in data-based estimates such as the Corelogic numbers, which use zip-code-level or county-level house price indices to estimate property values.

of household heads in the sample are married (74 percent) and have at least some college education (about 60 percent). Average household income is approximately \$110 thousand, while median income is \$87 thousand.

Panel B of Table 2 displays mortgage information. Households were asked how many months they were behind on their mortgage payments at the time of the PSID interview. Approximately 5.95 percent of mortgagors (N = 314) were 30+ days late on their mortgage payment, whereas 3.6 percent of mortgagors (N = 190) were at least 60 days late on their mortgage payment. In the remainder of the paper we adopt the definition of default that corresponds to two or more payments behind (that is at least 60+ days delinquent), as this is the convention in the literature. The average and median LTV ratio in the sample is 71 percent. LTV ratios are calculated as the sum of total liens on a residence (1st, 2nd, and 3rd) to self-reported home value. On average, households have about 21 years remaining on their respective mortgages and owe \$150 thousand. The average monthly mortgage payment is \$1,253, the average interest rate paid on first mortgages is just over 5 percent, and only 9 percent of first liens in the sample have adjustable rates. Almost 20 percent of households in the sample also have an outstanding second mortgage.

Panel C of Table 2 contains employment information. In our sample, 6 percent of household heads report being unemployed as of last year's survey date, while 8 percent report being unemployed as of the survey date or at some point during the year prior to the survey. Approximately 10 percent of households report that either the head or spouse was unemployed at the time of the survey, and 13 percent report that either the head or spouse was unemployed at some point during the prior year.

Panel D of Table 2 displays information on the nonhousing wealth of households at the time of the survey. Households hold \$20 thousand in liquid assets and \$127 thousand in illiquid assets on average,[8] and report, on average, approximately \$16 thousand in unsecured

[8] Liquid assets are defined as the sum of all checking or savings accounts, money market funds, certificates of deposit, government savings bonds, and Treasury bills. Illiquid assets are defined as the sum of equity and bond holdings, the value of automobiles, retirement accounts, and business income. These variables are measured only once, as of the survey date.

debt.[9] The wealth distribution is highly skewed in the sample, as the median household holds only \$5 thousand in liquid assets and \$12 thousand in illiquid assets (all from vehicles).

2.3. PSID Summary Statistics: Defaulters

The questions asked in the PSID regarding mortgage delinquency, employment, and the household balance sheet allow us to uniquely characterize defaulters in a degree of detail that is new to the literature. In Table 2 we also show summary statistics pertaining to the sample of households that are delinquent on their mortgages. Most notably, heads of household in default have an unemployment rate of 21 percent as compared to 6 percent for all mortgagors. If we consider unemployment among spouses, 31 percent of households in default had an unemployed spouse or head last year versus 13 percent for nondefaulters. Households in default are also significantly different along many demographic margins. For example, only 17 percent of defaulters attained a college degree versus 33 percent of all mortgagors, and 55 percent of households that default are married compared to 74 percent of all mortgagors. Furthermore, defaulters are relatively low-income households with income more than \$40,000 below that of the average mortgagor.

In terms of mortgage characteristics, the median household in default has an LTV ratio of 94 percent, while the average LTV ratio among defaulters is 101 percent. A much higher fraction of households in default have adjustable-rate mortgages (22 percent versus 9 percent of all mortgagors). Households in default pay a higher monthly mortgage payment and are faced with a higher interest rate on average. The average household in default is approximately five months behind on mortgage payments, while the median household in default is three months behind.

Panel D in Table 2 shows that households in default have significantly lower liquid and illiquid assets compared with the sample of all mortgagors. Households in default have approximately \$17 thousand less in liquid assets and \$92 thousand less in illiquid assets

[9] Unsecured debt is defined as credit card charges, student loans, medical or legal bills, and loans from relatives. Hospital bills includes outstanding debt owed to a hospital or nursing home.

than the average mortgagor. In addition, households in default have slightly more unsecured debt on average ($18 thousand versus $16 thousand)

The resounding message from this comparison is that households in default are far from the average mortgagor along almost every measurable dimension, particularly in terms of employment and wealth, which are unobservable quantities in most mortgage-level datasets.

3. Default and Household-Level Financial Shocks

In this section, we identify the relationship between household-level financial shocks and mortgage default. We use the full set of information on household income, wealth, employment status, marital status, and health status in the PSID to construct measures of adverse, household-level, financial shocks that may be important in generating variation in mortgage default behavior. We pay particular attention to employment shocks, as unemployment spells have been the focus in much of the previous literature.

We begin by constructing an unemployment shock, which we define as having a household head who reports being unemployed at the time of the survey or a spell of unemployment over the 12 months prior to the survey date. We also construct a spousal unemployment shock using the same definition. We define a "low liquid asset" shock as affecting a household that has insufficient liquid assets to cover one month's mortgage payment (23.8 percent of the sample falls into this category). We define a "high unsecured debt" shock as affecting a household that has unsecured debt greater than five years' worth of mortgage payments (5.1 percent of the sample falls into this category). A "high medical bills" shock is defined as having annual medical bills greater than one year's worth of mortgage payments (21.3 percent of our sample falls into this category), while a "high hospital bills" shock is defined as having annual hospital bills greater than one year's worth of mortgage payments (1.1 percent of the sample falls into this category). We define a "divorce shock" as having a household head who reports having gone through a divorce since the previous survey (15.8

percent of the sample falls into this category).

We also define several composite shocks such as 'cash flow' shocks (recent divorce, unemployment of head or spouse, or a 50 percent reduction in income) as well as generic 'any non-equity' shocks (recent divorce, unemployment of head or spouse, a 50 percent reduction of income, low liquid assets, high hospital bills, or high medical bills). Approximately 17 percent of the sample suffered a cash flow shock, and 57.4 percent of the sample suffered a generic non-equity shock.

3.1. Unconditional Default Rates by Shock Status

Table 3 describes both the default rates among households that suffered various shocks (Panel A), and the fraction of defaulters and nondefaulters that suffered each type of shock (Panel B). We see that the default rate associated with unemployed households (10.1 percent) is roughly triple that of employed households (3.0 percent). For households with and without negative equity, which we define here as an LTV ratio above 100 percent, the default rate for unemployed households is almost five times as high as for the employed. The largest difference in default rates is between households with and without low liquid assets.

Moving to Panel B of Table 3, we see that among households that defaulted 23.2 percent had heads who were unemployed, 42.1 percent had negative equity, 43.2 percent had a cash flow shock, and nearly 86.3 percent had a generic non-equity shock. Nearly two-thirds of households in default (66.8 percent) did not have enough liquid assets to meet a single monthly mortgage payment. These percentages are all significantly lower for households that did not default. Furthermore, approximately 6 percent of households in default experienced divorce compared with only 2 percent of nondefaulting households. In contrast, the difference in the incidence of the high hospital bill shock between the two types of households is much smaller (2.1 percent versus 1 percent).

Taken as a whole, the results reported in Table 3 imply that household-level employment and financial shocks are important determinants of mortgage default. Below, we show that this remains true when we condition on a host of borrower and loan characteristics.

3.2. Regression Results

In the previous section, we presented an analysis of unconditional default rates that was highly suggestive of the importance of household-level financial shocks in the default decision. In this section, we conduct a multivariate analysis, in which we control for numerous observable household and mortgage characteristics in an attempt to pinpoint which employment and financial shocks are most closely associated with household default behavior. We present estimates from linear probability models (LPMs) as well as logit models.

Columns (1) and (2) in Table 4 illustrate the basic relationship between the unemployment shock and the probability of mortgage default using an LPM. The dependent variable in each regression is a dummy variable corresponding to whether or not the household is in default. Column (1) does not include controls for demographics, mortgage characteristics, or geographic (state-level) differences, while column (2) includes controls.[10] The addition of controls approximately doubles the R^2 of the regression and has a nontrivial impact on the coefficient estimates associated with the unemployment shock, although it does not have a significant impact on the LTV ratio coefficient estimate. According to column (2), households with an unemployed head are about 5 percentage points more likely to default than households with an employed head, and households with both an unemployed head and spouse are about 9 percentage points more likely to default than an employed household. This is a huge effect considering the fact that the default rate across all households in our sample is only 4 percent. Equity in the house is also highly correlated with default. According to column (2), an increase in the LTV ratio of 20 percent is associated with a 1.9 percentage point

[10]The control set includes a complete set of race dummies, a gender dummy, a marriage dummy, dummies for educational levels, dummies for whether the state allows lender recourse and judicial foreclosure, and an indicator for whether the household lives in AZ, CA, FL, or NV, the states that experienced the largest house price declines and worst foreclosure problems. In addition, we add variables that measure state-level house price growth in the year prior to the survey and the change in the state unemployment rate over the same period. We also include controls for mortgage characteristics, which include the type of mortgage (adjustable rate vs. fixed rate), the interest rate, the remaining term, the presence of a second mortgage, and whether or not the mortgage is a refinance of a previous loan.

increase in the likelihood of default (0.2*0.094). To make things a bit more comparable, we can use the estimates in column (2) to determine the loss of equity that would cause the same increase in the propensity to default as an unemployment shock. According to the estimates, an unemployment shock to the household head is equivalent to an increase in the LTV ratio of roughly 56 percent (0.053/0.094), while an unemployment shock to the spouse is equivalent to a 43 percent (0.04/0.094) increase in the LTV ratio.

In column (3) of Table 4 we add additional financial shocks to the model to see whether other types of shocks are predictive of mortgage default. The inclusion of the additional shocks slightly decreases the estimated coefficients on the LTV and unemployment shock variables. The only shock that is statistically significant is the low liquid assets shock, which has an estimated effect on default that is similar in magnitude to the unemployment shock. The interpretation of the low liquid assets shock is unclear however, as it may be that financially distressed households run down their assets before choosing to default. If so, then the correct interpretation would be that households are experiencing other forms of financial distress and running down their assets, as opposed to suffering a direct shock to their assets that causes them to default. While the coefficient estimates associated with the other types of financial shocks are not statistically significant, the point estimates associated with the high hospital bills shock and the recently divorced shock are relatively large.

In column (4) we add an interaction term between the LTV ratio and the unemployment shock. The interaction is positive and statistically significant, reflecting the fact that for greater levels of negative equity, the impact of job loss on the likelihood to default is larger. An unemployment shock at a LTV ratio of 80 percent is associated with a 5.8 percentage point (0.8*0.1-0.022) increase in the propensity to default, whereas an unemployment shock at a LTV ratio of 1.2 is associated with a 9.8 percent (1.2*0.1-0.022) increase in the propensity to default.[11]

[11] Online Appendix D.1 estimates the region of interaction between equity and employment using Non-Linear Squares. Regions of moderate negative equity (LTVs between 88 and 125) exhibit strong interactions with employment. Outside of those LTV regions, we find no evidence of interactions.

Finally, columns (5) and (6) of Table 4 substitute state unemployment rates for the individual measures. As we discuss in the introduction, previous studies had to use aggregate unemployment rates, often at the state level, to proxy for unemployment shocks. Many of those studies found an extremely weak relationship between aggregate unemployment rates and default, which we also find. State unemployment rates by themselves and state-level rates interacted with LTV ratios are not correlated with default in our PSID sample. This confirms the claim by Gyourko and Tracy (2014) that using aggregate unemployment rates as a proxy for individual unemployment shocks results in a serious attenuation bias.

Table 5 displays estimation results using a logit model rather than an LPM. We report both average marginal effects (AMEs) in columns (1) and (2) and marginal effects at the mean (MEMs) in columns (3) and (4). In general, the results are similar to those obtained in the LPM. We see that in column (1), the estimated increase in the likelihood of default if the household becomes unemployed is 6.3 percentage points, on average. Likewise, the average increase in default rates from a 20 percent increase in LTV ratios is 1.36 percentage points (0.2*0.068). It is notable however, that the interaction between LTV ratios and unemployment is statistically insignificant in column (2). Turning to column (3), if we hold the covariates at their mean, unemployed households are 5.4 percentage points more likely to default, on average, than employed households, other things being equal. Likewise, if the LTV ratio increases by 20 percent the default rate is estimated to increase by 1.04 percentage points (0.2*0.052). In the Online Appendix (D.1), we explore the nonlinearity of this relationship in more detail.

3.2.1. Robustness: Alternate Definitions of Unemployment Shock

A potential criticism of the baseline results reported above is that the unemployment shock may be endogenous to the household rather than an entirely exogenous event. Some unemployment spells are voluntary and initiated by the employee, and it is possible that the estimated relationship between unemployment and default is driven by households that are defaulting due to some other event, which also happens to be characterized by voluntary job separation. To address this issue, columns (1) and (2) of Table 6 isolate job losses due to involuntary separations, which are defined in the PSID to be either a plant closure, strike/lockout, or layoff. The results are quantitatively similar to the benchmark results in Table 4. The point estimates remain essentially unchanged, with involuntary job loss being equivalent to a 53 percent decline in home equity. However, since there are only 220 instances of involuntary separation in our sample, the standard errors are slightly larger and the interaction term in column (2) is insignificant (the interaction term confounds the impact of involuntary job loss itself).

In the Online Appendix (C.1), we restrict the definition of an unemployment shock to involve those who are unemployed as of the survey date. This mitigates any concerns over the timing of job loss, and we still find results nearly identical to those in Table 4.

3.2.2. Robustness: Unobserved Heterogeneity

A similar potential criticism of the baseline results is that they may be driven by unobserved heterogeneity across households rather than reflecting a causal relationship from unemployment shocks to mortgage default. For example, perhaps some households are bad types and are just more likely to have members who are laid off and more likely to default. Impatient households whose members heavily discount the future may be more likely to default on debt and their heads and spouses may also be more likely to be fired due to poor work habits. If this unobserved factor does not vary over time, then the panel dimension of the PSID allows us to address the issue. To do so, we construct indicator variables based on the number of prior unemployment spells over the seven PSID surveys spanning 1994–2005, and include these variables in our control set.

Columns (3) and (4) of Table 6 display estimation results from a linear probability model that includes the prior unemployment shock indicator variables. The coefficient estimates associated with the LTV ratio variable and all of the financial shocks including the current unemployment shock dummy are largely unaffected. Unemployment is still equivalent to a 55 percent percent reduction in home equity.

3.2.3. Robustness: House Price Expectations

Another important factor in the household mortgage default decision, which is unaccounted for in the regressions discussed above and could confound the estimation results, is households' expectations of future house price movements. While the PSID does not contain direct measurements of house price expectations, we propose two indirect methods to control for expectations. The first is to assume that households have rational expectations, which implies that they do not make systematic errors in their forecasts. Operating under this assumption, we take self-reported house price growth in 2009–2011 for each of the households in the 2009 survey, and use it as a control variable. Columns (5) and (6) in Table 6 display the results. The inclusion of future self-reported house price appreciation does not materially affect the coefficient estimates associated with the unemployment variables or other financial shock variables.

Our second method for controlling for house price expectations is to assume that agents have adaptive expectations, and form their forecasts based solely on previous housing price dynamics. Based on this assumption, we control for lagged self-reported house price growth. Lagged self-reported house price growth is measured from 2007 to 2009 for households in the 2009 survey and from 2009 to 2011 for households in the 2011 survey. Columns (7) and (8) of Table 6 report the main set of results including lagged house price growth as a control. Again, we find that the inclusion of lagged house price growth does not materially affect the results.

3.2.4. Robustness: Survey of Consumer Finances

In the Online Appendix (B.1), we use the 2007–2009 Survey of Consumer Finances (SCF) panel dataset to double check our PSID results. Similar to the PSID, the SCF collected default information in the 2009 wave of interviews. However, the confounding factor in the SCF is the timing and precision of the questions. The main problems include the following: (i) the default question in the SCF refers to default over the last 12 months and is not confined to simply secured debt (let alone mortgages), (ii) there is no separate category for health expenses (the closest is medical loans, which are included with "other" loans), (iii) there are no data on consecutive unemployment spells, and (iv) since the default status at the survey date is unknown and since the SCF records negative equity, wealth, and employment as of the survey date, causal inference is nearly impossible. We use nearly identical sample restrictions for the PSID, limiting ourselves to working-age household heads who are mortgagors; however, it remains ambiguous as to whether the default occurred on the mortgage or on an unsecured line of credit. With these caveats in mind, we find similar results with the SCF as with the PSID data. Becoming unemployed is equivalent to a 50 percent reduction in equity. In specifications where we allow for an interaction between unemployment and equity, we find that unemployment nearly triples the impact of any given equity loss on default propensity. Online Appendix B.1 includes a more thorough explanation of these results.

3.2.5. Robustness: Generic Cash Flow and Non-Equity Shocks

Table 7 illustrates the impact of cash flow shocks, generic non-equity shocks, and income loss on the propensity to default. Columns (1) and (2) show that the presence of a cash flow shock (unemployment of head or spouse, divorce, or 50 percent income loss) is equivalent to a 55 percent reduction in equity. In column (2) we allow for the cash flow shock to interact with the loan to value ratio. We find a significant interaction between the cash flow shock and LTV. The effect of an equity reduction is nearly twice as large in the presence of a cash flow shock. Columns (3) and (4) allow for generic "any non-equity" shocks. In general, we find very similar results to the cash flow shock. Columns (5) and (6) include a dummy for a 50 percent income decline. Once again the magnitude of the results is quite similar, with an income decline being equivalent to a 71 percent decline in equity. The interaction term in column (6) between equity and severe income loss is insignificant, likely due to the low incidence of such large drops in income.

4. Do Too Many Borrowers Default or Too Few? Double Trigger and Strategic Default

Our analysis above finds strong evidence that unemployment and household-level financial shocks play an important role in a household's decision to default on its mortgage. This is important, as it confirms the suspicions of many researchers and market participants who have long believed that employment status and financial health are important determinants of a household's decision to default. In this section, we focus on a simple model of default known as "double trigger" model and discuss its implications, particularly with respect to what is known as strategic default.

As background, there are two standard ways that researchers have thought about mortgage default. The first is to treat the house as a financial asset and use asset pricing techniques from finance (which we discuss in more detail in the next section). The second is a heuristic commonly referred to as the double trigger model.[12] The two triggers in "double trigger" are negative equity and an individual household shock. The idea is that negative equity is a necessary condition for default, as the household will never default with positive equity because it can sell the house. The sufficient condition is that the household suffers a "life event," which results in the inability to continue making mortgage payments. Double trigger is not an optimizing model, but, as we will argue below, it underpins a lot of important thinking about the subject.

How does the double trigger model stack up against the data? At first blush, the answer

[12]See Section 5 for a discussion of both types of models, and see Online Appendix A.1 for a theoretic exposition of both types of models.

appears to be reasonably well. In the analysis above we found that both equity levels and household-level employment and income-related shocks are important predictors of mortgage default. In addition, we found some evidence that the combination of the two factors further increases the probability of default (Table 4 and Table 6), so that households with the combination of negative equity and a life event appear to be much more likely to default than those that face either negative equity or a life event but not both. Thus, it is tempting to conclude that the simple double trigger model is a reasonable approximation to the data.

However, further analysis generates a more nuanced and striking view of the data. The starting point here is that, according to double trigger, if we focus on borrowers with negative equity, the inability to pay is necessary and sufficient for default. If we divide negative equity borrowers into those that "can pay," meaning that they have sufficient financial resources, either in terms of flow of income or stock of assets, to pay their mortgage payment and those that "can't pay," those that do not, default should occur only for the "can't pay" borrowers. Figure 3 illustrates this by dividing negative equity borrowers by whether they can or cannot pay and whether they did or did not pay. According to the double trigger model, only the diagonal elements of the figure should be populated. As far as that model is concerned, we can view the off-diagonal elements as errors. Type I error, the upper right corner, corresponds to borrowers that the model predicts will pay, but don't, and Type II error, the lower left corner, corresponds to borrowers that the model predicts won't pay but that continue to pay.

What we call Type I error here, households that can pay but don't, has generated considerable attention among both academics and policymakers, who refer to them as "strategic defaulters." Researchers, including Guiso, Sapienza, and Zingales (2010), Bhutta, Dokko, and Shan (2011), Keys et al. (2012), have focused on identifying borrowing households that appear to be able to pay but choose instead to default. Type II error, borrowing households that can't pay, but do, has, on the other hand, received comparatively very little attention.

The challenge in bringing the double trigger model to the data is the phrase, "can't pay."

To an economist, “can't pay” means that the mortgage payment is beyond the household's budget set. In other words, even if the household sold all of its worldly possessions, starved, and borrowed the maximum possible amount from available creditors, it would not be able to make the payment. But in common usage, and for the heuristic of the double trigger model, it is more appropriate to think that a borrower can't pay if paying involves an unreasonable sacrifice. A borrower can pay, on the other hand, if paying involves what we would think of as a reasonable sacrifice.

In the remainder of this section, we attempt to identify “can't pay” and “can pay” households in our data and then, using these definitions, we assess the importance of strategic defaulters (Type 1 error) and borrowers that continue to pay despite appearing to lack the financial means to do so (Type II error). Overall, we find the evidence on whether the data support the double-trigger theory of mortgage default to be mixed. While Type I error is extremely small in our data, Type II error is widespread.

4.1. Identifying “Can Pay” and “Can't Pay” Households

In taking the idea of “can pay” and “can't pay” borrowers to the data, we confront two issues. The first is that, as mentioned above, whether a borrower “can pay” or “can't pay” a mortgage payment is a matter of opinion, and any definition is somewhat arbitrary. As a result, we come up with very strict definitions of “can pay” and “can't pay” that we think most reasonable people would agree with. The second problem is timing. Ideally, we would like to have all relevant information as of the same moment in time. For example, to assess whether the borrower can pay *this month* we would like to know whether the borrower is delinquent *this month* and how much income the borrower has *this month*. However, in the PSID, information on income is provided only for the calendar year prior to the survey year, whereas wealth and employment information are reported as of the survey date. For example, we will know if a particular household had no income last year but we have no information on whether it was delinquent on its mortgage payments last year. Alternatively, we know if the household is delinquent and whether it is employed or unemployed at the survey date, but we do not how much income it has at that time. With these two issues in mind, our baseline definitions are:

(1) **Can Pay:** Head of household is employed as of the survey date and the household has at least six months' worth of mortgage payments in stock, bonds, or liquid assets net of unsecured debt.

(2) **Can't Pay:** Head of household is unemployed as of the survey date and the household has less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt.

Table 8 displays a detailed set of summary statistics for each category. The first thing to note is that because our definitions are quite strict, the "can pay" and "can't pay" categories are not even close to exhaustive. The two categories combined account for slightly less than half of our PSID sample.[13] Panel (A) describes the demographics and income of each subset of households. The "can pay" households have median annual gross family income of $110k, almost twice as large as the "can't pay" households, which have a median annual gross family income of about $58k. The "can pay" households are significantly more likely to be college educated and have, on average, fewer children. In addition the "can't pay" group is made up of a much higher fraction of minority households, and is more likely to include single households and households headed by a woman.

If we focus on the subsets of can and can't pay borrowers that default, we find that, regardless of whether they can or can't pay, defaulters are more likely to be minority households, are more likely to be single households, and are more likely to be headed by a female than their nondefaulting counterparts. In addition, they have less income, on average, than their nondefaulting counterparts. However, in comparison with each other, there are some

[13]Online Appendix E.1 provides the same detailed analysis as this section, using different definitions of "can't pay" and "won't pay" households, including collectively exhaustive and mutually exclusive definitions. The main results obtain in each case: about one-third of the "can't pay" default, around 1 percent to 3 percent of "can pay" households default.

striking differences. "Can pay" households that default have more than twice as much income on average, are much better educated, are more likely to be headed by a male, and are significantly more likely to be black that "can't pay" households that default.

Panel (B) of Table 8 displays basic mortgage characteristics. On average, we see in the panel that "can pay" households hold significantly larger loans than "can't pay" households. "Can pay" households, on average, have significantly lower LTV ratios, lower mortgage rates, are more likely to have a fixed rate mortgage, and are more likely to have a refinanced loan. Defaulters, for both can and can't pay subsets, are much more likely to have ARMs than nondefaulters. Panel (B) shows that the "can pay" borrowers that default have a mean LTV of 1.25 and a median closer to 1. In contrast, the mean and median LTV ratios associated with the can't pay borrowers are below 1.

Panel (C) of Table 8 describes the employment status of the head and spouse for each category. Since employment of the head is used to define the groups, it is largely degenerate. Only 2 percent of "can pay" households had a head who was unemployed at some point last year and subsequently employed as of the survey date (recall that this is a condition for being in the "can pay" group). Spouses in the "can't pay" households who default as well as those in the "can pay" category who default are much more likely to be unemployed as of the survey date than spouses in nondefaulting households.

Panel (D) of Table 8 describes the wealth of each category. On average, the "can pay" subgroup has significant holdings of stocks, bonds, and liquid assets. On the other hand, by construction, the "can't pay" subgroup has virtually no assets, with median liquid asset holdings of only $500. The "can pay" subset of households that default have lower liquid assets than their nondefaulting counterparts, but compared with the "can't pay" subgroup, these households have significantly more of every category of asset.

4.2. Default Behavior of Can and Can't Pay Borrowers

The first row of Table 9 shows that only about 1 percent of "can pay" households actually default compared with 19 percent of "can't pay" households. Of course, this implies that 99 percent of "can pay" households are not in default, while more than 80 percent of "can't pay" households continue to make their mortgage payments. The double trigger model implies that we should further restrict our attention to borrowers with negative equity. The second row of Table 9 shows that if we focus on borrowers with negative equity, the share of "can pay" borrowers that default rises to 5 percent and for "can't pay" borrowers it rises to 33 percent.[14] Returning to our language from above, we see that Type I error is quite small. Of the borrowers that the double trigger model predicts should pay, approximately 95 percent actually do pay. In contrast, Type II error is huge. According to the double trigger model, "can't pay" borrowers should default, but the data show that about two-thirds of them continue to pay. We now discuss Type I and Type II error in turn.

4.2.1. Type II Error: Why Do So Few Unemployed Households with No Savings Default?

One possibility for why we find so few defaults among "can't pay" households is that our definition isn't strict enough. In Rows (3) to (6) of Table 9, we show default rates using a definition of "can't pay" in which *both* the head and spouse are out of work, and the household has less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. We find that the share of defaults conditional on having negative equity actually goes down slightly from 33 percent to 30 percent. In other words, approximately 70 percent of households in negative equity positions, in which both the head and spouse are unemployed, and in which household liquid assets are less than one month's mortgage payment are current on their mortgages.

[14] Table 9 also shows that these results hold true even if we lower the cutoff for negative equity to a combined loan to value ratio of 0.9.

To understand the "can't pay" households better, we estimate the effect of equity on default for only the subsample of "can't pay" households. A priori, we would expect that if these households are truly unable to afford making their mortgage payments, then equity should not play any role whatsoever in that decision, and thus, we should not find a correlation across "can't pay" households between equity and the propensity to default. Table 10 reports estimates of linear probability models in which a default indicator is regressed on LTV ratios along with the same demographic controls and state controls that were used in the baseline regressions presented in Section 3. The first two columns of Table 10 display regression results for the "can't pay" households, while the last two columns display results for the "can pay" households. Unsurprisingly, we see that the decision to default for the "can pay" households is negatively correlated with the amount of equity in their properties. All relevant theories of mortgage default predict that equity should be one of the primary determinants of optimal mortgage default for unconstrained borrowers. The results for the "can't pay" households are fairly striking though. While the precision of the LTV coefficient estimates is low due to the small sample size of the "can't pay" group, the point estimates are more than twice as large as those for the "can pay" group of households. Thus, it appears that the default decision for "can't pay" households may be even *more* sensitive to equity levels than the decision for "can pay" households.

One obvious concern about the estimated magnitude of Type II error here is the small PSID sample. Is it reasonable to extrapolate these numbers to the broader population of underwater mortgage borrowers? To address this issue, we compare them with aggregate data. In 2009, the Bureau of Labor Statistics (BLS) reported that there were about 15 million unemployed workers, and the Mortgage Bankers Association (MBA) reported that there were about 2.7 million loans that were more than 60 days past due. This implies that, in 2009, unemployed workers outnumbered past due households by a ratio of about 5:1. This 5:1 ratio is about the same as the ratio of all "can't pay" homeowners to delinquent "can't pay" homeowners in our PSID data. While these ratios are in no way dispositive, the point is that the aggregate data also display a similarly low number of defaults relative to distressed households.

It is also worth noting that the PSID dataset, while not perfect, is better, in many cases, than the data available to market participants. Unlike borrowers applying for loans, who have an incentive to overstate their income, or delinquent borrowers applying for relief from their lender, who have an incentive to understate their income, PSID participants have no incentive to lie about their employment status or income. We return to this topic when we discuss policy implications later in the paper.

On the face of it, it seems hard to believe that borrowers with no job and little to no savings could and would continue to pay their mortgages. However, the PSID does not contain information on households' access to credit. Credit could come in the form of unsecured debt from lenders or it could come less formally from family members or friends. To shed light on these issues, we turn to two additional data sources. In the 2011 PSID, we have disaggregated data on loans from family members. We find that loans from family members are rare, and only about 10 percent of the "can't pay" defaulters and fewer than 10 percent of the overall defaulter population in the PSID received assistance in this form (see Online Appendix F.1). To address the issue of access to more formal credit markets, we turn to the SCF.[15] In the SCF, we find that defaulters have less than one half of one month's mortgage payment available in unused credit. Because of several outliers, the average unused credit for a defaulter is approximately three months of mortgage payments. While this evidence is not conclusive, it does suggest relatively limited roles for family lending and unsecured borrowing among defaulters.

One potential explanation for the lack of default among households that have what appears to be an empty budget set, is that households are able to liquidate vehicles and other hard-to-sell assets. In Table 11 we can see that defaulters have a significant amount of illiquid assets. Illiquid assets include stocks, bonds, vehicles, business assets, and retirement

[15]In the SCF, as mentioned above, the default data suffer from severe time aggregation bias. In addition, the type of defaulted debt is not specified.

assets. The median defaulter can make 6.37 months' worth of mortgage payments with illiquid assets, and the 25th percentile can make 2.5 months' worth of mortgage payments with illiquid assets. To test whether or not these households are running down illiquid asset holdings, we would need high-frequency panel data on the wealth holdings of households in default, such data are not available in any existing surveys.

4.2.2. Type I Error: Evidence of Strategic Default

As already mentioned, our measure of Type I error is known in the popular press and among many academics as "strategic default." While there is no consensus in the literature on an exact definition of strategic default, the term is often interpreted to describe a borrower in a position of negative equity who has plenty of financial resources to continue to make mortgage payments, but instead chooses to default. For example, Mian and Sufi (2009) define instances of strategic default as "defaults where a borrower has the cash flow to make mortgage payments, but chooses to default nonetheless because of negative equity in the house." Similarly, Guiso, Sapienza, and Zingales (2010) define the concept as "households' propensity to default when the value of their mortgage exceeds the value of their house even if they can afford to pay their mortgage."

Our data suggest that strategic default is rare. We find that fewer than 1 percent of "can pay" households default on their mortgages. If we focus our attention on "can pay" households with negative equity, this percentage does rise, but only slightly, to about 5 percent. We now use the detailed data on wealth in the PSID to elaborate on the extent of strategic default in the data. Table 11 presents information on the wealth distribution of households that default with negative equity. The table displays information on the liquid asset distribution, the illiquid asset distribution, the distribution of the sum of liquid and illiquid assets net of unsecured credit owed, which we refer to as net nonhousing wealth, and the distribution of the sum of liquid assets and stocks and bonds. We normalize everything by the monthly mortgage payment and show both unweighted (Panel A) and weighted (Panel

B) summary statistics. This table shows a few notable patterns. First, the vast majority of households that default with negative equity have very low levels of liquid assets. The median household in default with negative equity can make only approximately one-third (unweighted) to two-thirds (weighted) of one monthly mortgage payment with its liquid assets, while 75 percent of these households do not have enough liquid assets to make two payments, and 90 percent report having liquid asset levels that are less than four mortgage payments.

While very few negative equity defaulters have high levels of liquid assets, a nontrivial fraction of them have relatively high levels of illiquid assets. According to the table, 25 percent of these households hold more than 18 months' worth of mortgage payments in illiquid assets, while 10 percent hold more than 30 months' worth. These numbers drop a bit when we net out unsecured debt levels. Should we interpret these statistics as evidence that many households are strategically defaulting? Before jumping to any conclusions, it's important to remember that illiquid assets are, by their nature, costly to access. Recall that we define illiquid assets in this paper to include equity and bond holdings, the value of automobiles, retirement accounts, and business income. It may be relatively easy to liquidate equity and bond positions, but withdrawing from a retirement account and selling a car can be very costly propositions, especially if owning a car is necessary to remain employed. In the last row of each panel we report the distribution of liquid assets combined with stock and bond holdings, which we believe are likely the easiest of the illiquid assets to access. This distribution looks very similar to the distribution of liquid assets only. For example, 75 percent of negative equity households have less than two months' worth of mortgage payments in liquid assets plus stock and bond holdings.

For comparison purposes, Table 12 displays the same statistics for nondefaulting households. The differences in the distributions are striking. The median household that is not in default holds approximately five months' worth of mortgage payments in liquid assets, and more than 20 months' worth of payments in illiquid assets. The nondefaulting households hold significantly higher levels of wealth than the negative equity defaulters. Our takeaway from Tables 11 and 12 is that there is minimal evidence of strategic default in the data, as the vast majority of negative equity defaulters have very little wealth. To the extent that there are some negative equity defaulters that do have nontrivial levels of wealth, most of that wealth appears to be in forms that are highly illiquid. Thus, our interpretation of the data is that strategic default and Type I error are quite small in reality.

5. Implications for Research and Policy

In this section, we first discuss the implications of our analysis for the study of household mortgage default decisions. We then show that these findings illustrate the challenges of assisting distressed borrowers in a housing crisis.

5.1. Modeling Default

Our starting point here is the double trigger model discussed in the previous section. Double trigger has the advantage of being simple, and it gets some key features of the data right. First, the double trigger model predicts that job loss and other household-level shocks increase the likelihood of default. While this may seem obvious, another workhorse model, which we discuss below, predicts that individual household shocks should have no effect on the probability of default. The second success of the double trigger model is that it predicts that borrowers who can pay their mortgages will pay their mortgages and, as we showed in the last section, that is not a bad approximation to the data. Specifically, we showed that approximately 99 percent of borrowers with ample income and considerable savings made their mortgage payments and that conditioning on negative equity resulted only in decreasing that share to 95 percent. However, the double trigger model fails along two key dimensions. The first is that the double trigger model implies that the effect of equity on default is binary. In particular, it predicts that any strictly positive level of equity is sufficient to prevent default.

But Panel (A) of Figure 2, which plots the default rate among employed and unemployed households as a function of equity, shows that regardless of whether borrowers are employed or not, their behavior is sensitive to the precise level of equity in the house. Less equity implies more default even at very high levels of negative equity. The second problem is that the double trigger model predicts that all "can't pay" borrowers should default but, as we documented in the previous section, most do not.

An alternative to double trigger is the "frictionless option model" (FOM), which has been the standard theoretical treatment of the topic since Asay (1979), who was the first to apply the option pricing model of Black and Scholes (1973) to mortgages (see also Kau, Keenan, and Kim (1993) and Kau and Keenan (1995)). The FOM assumes that households have unlimited opportunities to borrow and save at the riskless rate and can hedge both the house price and the interest rate risk associated with the mortgage. The main result of the FOM is that one can treat the combination of the house and the mortgage as a call option. The borrower sells the house to the lender and receives a call option to buy the house back from the lender by paying a strike price equal to the outstanding balance on the mortgage. If the value of the call exceeds the monthly payment on the mortgage, then the borrower makes the payment; if the value of the call falls short, and if the borrower cannot sell the house for more than the outstanding balance, then the borrower defaults. The key insight of the model is that the value of the call depends only on the interest rate and house price process and not on the borrower's individual situation. Borrower income, borrower assets, borrower employment, and even borrower beliefs about house prices do not matter in the model.

The FOM succeeds in one key respect. In the double trigger model, the threshold level of LTV for default is 100, whereas in the FOM the threshold LTV almost always exceeds 100. To understand why, recall that the basic intuition is that the mortgage is a call option. Negative equity simply means that the call option is out of the money, but the great insight of option theory is that an out-of-the-money option is typically worth more than zero, so with a sufficiently low mortgage payment, it always makes sense to continue paying. For any two identical mortgages on identical houses, the FOM predicts a unique threshold LTV, but in the data we would expect to see a distribution of threshold LTV levels and a continuous relationship between LTV and default, which is what we see in Figure 2 for both "can pay" and "can't pay" borrowers.

The FOM fails along two dimensions. First, the prediction of the FOM that borrower employment does not affect default is at odds with the data. Our findings show that conditional on a level of negative equity, unemployed borrowers are three times as likely to default as employed borrowers, whereas, according to the FOM, individual employment status should have no predictive power at all.

The second failure of the FOM has to do with the "can pay" borrowers. Unlike the double trigger model, the FOM predicts that some "can pay" borrowers will default, and in fact, under reasonable parameterizations, the model predicts that many of the "can pay" borrowers will default. For example, Kau, Keenan, and Kim (1993), in their baseline example, calculate that 100 percent of borrowers with LTV ratios above 115 percent will default. That prediction is difficult to reconcile with our finding that among "can pay" borrowers, only 5 percent of borrowers with negative equity default on their payments. In addition, Panels (A) and (B) of Figure 2 show that default rates in our data never exceed 25 percent, even for the subsample of households with LTV ratios above 150 percent that have not suffered an employment or cash flow shock.

To improve on the FOM, researchers have built dynamic models of households that maximize lifetime utility, consume both goods and housing services, and finance the purchase of homes with mortgages on which they can default.[16] The key innovation is that these models include an array of realistic frictions including borrowing constraints, risks that cannot be fully hedged, moving costs, and, typically, default penalties that often include losing access to mortgage markets for a specified period of time. As a result, we refer

[16] Examples include Corbae and Quintin (2009), Garriga and Schlagenhauf (2009), Chatterjee and Eyigungor (2011), Campbell and Cocco (2011), Hedlund (2011), Schelkle (2011), and Laufer (2012).

to these models as *frictional models*. It is important to stress that the basic logic that a mortgage is a call option still applies here. In a sense, the FOM is just a special case of these models with all of the constraints stripped away.

In discussing frictional models, it is useful to separate out the effects of borrowing constraints, because they are different from the effects of other frictions. If we consider a model in which households have stochastic labor income and face borrowing constraints, the similarities and differences with the FOM are easy to explain. Recall that in the FOM, the borrower trades off the cost of making the mortgage payment against the benefit of the payoff of the call option on the house at some future date. If a household faces a binding borrowing constraint, then, all else being equal, the marginal utility of current consumption is higher. As a result, the cost of the mortgage payment rises relative to the payoff on the call option and default becomes more attractive.

Introducing borrowing constraints produces a model that is more realistic than both the FOM and double trigger models along two key dimensions. On one hand, it improves on the FOM because borrowing constraints mean that shocks to a household's financial condition now matter. Thus, the model can, like the double trigger model and unlike the FOM, rationalize the strong effects of employment and financial shocks that we see in the data. On the other hand, even in the presence of borrowing constraints, the basic intuition of the FOM that the LTV default threshold does not equal 100 still holds. In other words, we would still expect there to be a continuous relationship in the data between LTV and the probability of default.

There is one problem, however, that borrowing constraints cannot solve, which is that the number of defaults predicted by the model will still vastly exceed what we observe in the data. For the households not facing borrowing constraints, the predictions in Kau, Keenan, and Kim (1993) still imply that all borrowers will default if the LTV exceeds 115, as we discuss above. But, for households suffering shocks, the threshold LTV will be even lower, which, again, is completely at odds with what we see in the data.[17]

The frictional models recognize that borrowing constraints alone cannot make the model realistic and so they introduce the additional frictions mentioned above. The key point about these other frictions—moving costs, the inability to obtain another mortgage, and others—is that they make default much *less* attractive. As a result, some of these frictional models can generate the low default rates that we observe in the data.

However, the problem with introducing these frictions is that they are something of a black box. Laufer (2012), for example, structurally estimates the implied rent-to-price ratio that defaulters face in the rental market, writing that:

> The rent-price ratio that prevails in the post-default rental market is $\rho = .17$, which equals 0.68 in annual terms. This estimate captures not just the true cost of rental housing but all the costs associated with default, including the distaste for renting, the impact on the homeowners' credit score, and any potential stigma. This value is approximately 10 times the true rent-price ratio, indicating a high cost of default.

In other words, the parameter ρ captures a list of things that researchers cannot measure, and Laufer's estimate of the parameter implies that they must be very large.

In addition, there is reason to believe that these frictions may differ enormously across households. In other words, dispersion in costs could explain why some "can't pay" borrowers stick it out while others do not.

There are other potential explanations for these patterns that have been offered in the literature, which involve variables that we do not observe in the PSID. A priori, access to either unsecured credit markets or to the wealth of relatives/friends could play an important role. However, as we discuss in Section 4.2.1, there is relatively little evidence of loans from relatives in the 2011 PSID (which specifically tracks these types of loans), and the SCF reveals that the median defaulting household has relatively little unused credit available. In

[17] In Online Appendix A.1 we build a model that nests these three major theories (frictionless, double trigger, and portfolio constraints) and provides an additional comparison of these models' predictions to data. In each case, the model over-predicts defaults relative to the data in regions of severe negative equity.

addition, unsecured borrowing is usually very expensive. For example, the Flow of Funds reports that interest-bearing credit accounts were assessed nominal interest rates between 12.95 percent and 14.68 percent during the Great Recession. While much family assistance may be "off the books," it's not clear whether either unsecured credit or family assistance alone could explain the fact that 80 percent of the "can't pay" households in our sample continue to make payments. However, there may be other unobservable factors in play, which, combined with other unobserved credit markets, could explain these low default rates.

One possibility along these lines is that many households have a strong moral aversion to defaulting on debt, especially mortgage debt. For example, Guiso, Sapienza, and Zingales (2010) find evidence in survey data that many households consider strategic mortgage default to be an immoral practice, and as a result, are much less likely to engage in such behavior.[18] Approximately 82 percent of the households in their survey report having a moral aversion to mortgage default, so it is conceivable that a large majority of our "can't pay" households hold similar reservations against default.

Another possibility is that many households have a strong attachment to their homes, and thus go to extreme measures to avoid default and foreclosure by drawing down their illiquid assets such as vehicles and retirement accounts. Finally, optimistic expectations of future house prices may play an important role. The theoretical literature tells us that house price expectations are an important determinant in the decision to default. While it's hard to believe that optimistic expectations alone could explain why 80 percent of households with no income or assets continue to make payments, such an explanation is at least consistent with the evidence on the sensitivity of default decisions to equity displayed in Table 10.

5.2. The Problem of Loss Mitigation

When a lender forecloses on a loan, the lender's losses are typically quite substantial. For starters, the collateral is typically worth less than the outstanding balance on the loan. In

[18] The definition of strategic default used by the authors is a scenario in which a borrower can afford to make the mortgage payment, but chooses not to.

addition, the foreclosure process takes a long time during which the lender receives no income from the loan and incurs substantial administrative costs. Many argued during the financial crisis in 2008 that the losses on foreclosures were so large that lenders could save money by renegotiating mortgages and giving borrowers payment or principal reductions that both avoided foreclosures and saved money for investors. To see this formally, we follow Foote, Gerardi, and Willen (2008) and consider a lender with a borrower who owes m dollars on a house currently worth p_h dollars and who will default with probability α_0, in which case the lender recovers p_h less λ dollars in foreclosure costs. A modification lowers the value of the loan to $m^* < m$ and the probability of foreclosure to $\alpha_1 < \alpha_0$. Some simple arithmetic shows that the modification is both profitable for investors and prevents foreclosure if:

$$\underbrace{(\alpha_0 - \alpha_1)}_{\substack{\text{Reduction in} \\ \text{foreclosure prob.}}} \times \underbrace{(m^* - (p_H - \lambda))}_{\substack{\text{Reduced} \\ \text{loss}}} > \underbrace{(1 - \alpha_0)}_{\substack{\text{Pct. repay without} \\ \text{mitigation}}} \times \underbrace{(m - m^*)}_{\substack{\text{Reduced value of} \\ \text{the mortgage}}} . \tag{1}$$

The left-hand side measures the gain to investors resulting from foreclosure prevention: for measure $\alpha_0 - \alpha_1$, investors recover $m^* > p_H - \lambda$. The right-hand side, however, measures a cost that is often ignored in discussions of renegotiation. For the measure $1 - \alpha_0$ set of borrowers who would have repaid their loans in full either way, the lender now recovers $m* < m$.

To understand why our findings above are relevant to renegotiation, suppose that the double-trigger model is an accurate description of borrower behavior. In that case, if we observe borrowers who have negative equity and are suffering from adverse income/financial shocks, we will know that all of those borrowers will default on their respective mortgages. In other words, α_0 would equal 1, meaning that the right-hand side of equation (1) would equal zero. As a result, the lender could, in principle, prevent *all* foreclosures and increase profits.

The challenge for renegotiating loans, generated by our findings regarding the extent of Type II error, is that α_0 is significantly smaller than 1. To illustrate the point, suppose that we take an estimate of $\alpha_0 = 1/3$, which is at the high end of the default rate that we estimated for "can't pay" borrowers with negative equity, and suppose we assume that $\alpha_1 = 0$, meaning that renegotiation prevents all foreclosures (that is, re-default rates are zero). Then, for renegotiation to be profitable the following condition must hold:

$$\frac{m^* - (p_H - \lambda)}{m - m^*} > \frac{(1-\alpha_0)}{(\alpha_0 - \alpha_1)} = \frac{2/3}{1/3} = 2, \tag{2}$$

which implies that:

$$m - m^* < (1/3) \cdot (m - (p_H - \lambda)). \tag{3}$$

In other words, the maximum profitable reduction in debt is one-third of the difference between what the borrower owes and the recovery value from foreclosure. To see the problem, consider a borrower with an LTV ratio of 150 percent and assume that the lender can recover only 75 percent of the value of the house through foreclosure (the average foreclosure recovery rate is 78 percent as reported by Pennington-Cross (2006)). Equation (3) implies that the maximum possible modification would only lower the balance to an LTV ratio of 125 percent.[19]

To make matters worse, our data involve a sample of borrowers who have no incentive to lie about their income and employment. For lenders, the challenge of equation (1) is compounded by the fact that borrowers have every incentive to understate their income and employment. In other words, our figure of a one-third probability of default for borrowers who report no income and employment may well be high, relative to what we would obtain if we used what borrowers report to their lenders rather than to the PSID interviewers. Indeed, for the Home Affordable Modification Program (HAMP), the government's signature foreclosure prevention program, documentation of income was the most significant obstacle

[19] One seemingly obvious solution to this issue, which was often adopted in practice, is for lenders to only renegotiate with borrowers who have missed a few mortgage payments and thus are already delinquent on their loans. However, conditioning on delinquency creates the incentive for borrowers to strategically miss mortgage payments, a moral hazard problem that has been documented in the literature (Mayer et al. (2014)).

to facilitating renegotiation.[20]

6. Conclusion

In order for policymakers to respond to the 2007–2009 foreclosure crisis, it is necessary to understand the sources of mortgage default. While there is broad agreement that a number of factors may potentially contribute to default, including equity, employment, and liquidity, due to data limitations (particularly in terms of the employment status of the household), it has been impossible to directly test the relative importance, as well as interactions, among such factors. In this paper, we make three contributions to the literature. First, we use new household-level data to quantitatively assess the roles that: (i) job loss, (ii) negative equity, and (iii) other financial shocks play in default decisions. In sharp contrast to prior studies that proxy for individual unemployment status using regional unemployment rates, we find that unemployment is one of the most important determinants of default. Job loss by the head of household is equivalent to a 56 percent reduction in home equity. Second, we show that while household-level employment and financial shocks are important drivers of mortgage default, the vast majority of distressed households (approximately 80 percent) do not default on their respective mortgages. This finding has important implications for theoretical models of mortgage default and the optimal design of loss-mitigation policies. It is unclear why so many households in extreme financial distress continue paying their mortgages, but hopefully, future research will provide insight on this crucial question. Finally, we provide evidence in the data on the importance of strategic default. We find only a minimal role for strategic default, as most households that default have very low wealth levels, and most households in positions of negative equity with relatively high wealth choose not to default.

[20] See "The mod squads; Treasury unleashes loan-relief 'SWAT teams.' Will it help?" *Washington Post*, 2 December 2009.

References

Asay, M.R. 1979. "Rational Mortgage Pricing." Tech. rep., Ph.D. dissertation. University of Southern California, Los Angeles.

Bajari, Patrick, Chenghuan Sean Chu, and Minjung Park. 2008. "An empirical model of subprime mortgage default from 2000 to 2007." Tech. rep., National Bureau of Economic Research.

Benítez-Silva, Hugo, Selcuk Eren, Frank Heiland, and Sergi Jiménez-Martín. 2008. "How well do individuals predict the selling prices of their homes?" Levy Economics Institute Working Paper.

Bentolila, Samuel and Andrea Ichino. 2008. "Unemployment and consumption near and far away from the Mediterranean." *Journal of Population Economics* 21 (2):255–280.

Bhutta, Neil, Jane Dokko, and Hui Shan. 2011. "Consumer ruthlessness and strategic default during the 2007-2009 housing bust." Federal Reserve Board of Governors Working Paper.

Black, F and M. Scholes. 1973. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy* 81:637–654.

Böheim, René and Mark P Taylor. 2000. "My home was my castle: evictions and repossessions in Britain." *Journal of Housing Economics* 9 (4):287–319.

Campbell, J.Y. and J.F. Cocco. 2011. "A Model of Mortgage Default." Tech. rep., National Bureau of Economic Research.

Campbell, Tim S and J Kimball Dietrich. 1983. "The determinants of default on insured conventional residential mortgage loans." *The Journal of Finance* 38 (5):1569–1581.

Chatterjee, S. and B. Eyigungor. 2011. "A quantitative analysis of the us housing and mortgage markets and the foreclosure crisis." Federal Reserve Bank of Philadelphia Working Paper.

Corbae, D. and E. Quintin. 2009. "Mortgage Innovation and the Foreclosure Boom." Unpublished paper, University of Texas at Austin.

Deng, Yongheng, John M Quigley, and Robert Order. 2000. "Mortgage terminations, heterogeneity and the exercise of mortgage options." *Econometrica* 68 (2):275–307.

Deng, Yongheng, John M Quigley, Robert Van Order, and Freddie Mac. 1996. "Mortgage default and low downpayment loans: the costs of public subsidy." *Regional Science and Urban Economics* 26 (3):263–285.

Elul, R., N. Souleles, S. Chomsisengphet, D. Glennon, and R. Hunt. 2010. "What'Triggers' Mortgage Default?" FRB of Philadelphia Working Paper No. 10-13.

Epperson, James F., James B. Kau, Donald C. Keenan, and Walter J. Muller III. 1985. "Pricing Default Risk in Mortgages." *Real Estate Economics* 13 (3):261–272.

Experian and Oliver Wyman. 2009. "Understanding Strategic Default in Mortgages Part I." *Experian-Oliver Wyman Market Intelligence Report 2009* Topical Report Series.

Foote, Christopher L, Kristopher Gerardi, and Paul S Willen. 2008. "Negative equity and foreclosure: Theory and evidence." *Journal of Urban Economics* 64 (2):234–245.

Foster, Chester and Robert Order. 1985. "FHA terminations: A prelude to rational mortgage pricing." *Real Estate Economics* 13 (3):273–291.

Garriga, C. and D.E. Schlagenhauf. 2009. "Home Equity, Foreclosures, and Bailouts." Manuscript, Federal Reserve Bank of St. Louis.

Gathergood, John. 2009. "Income shocks, mortgage repayment risk and financial distress among UK households." Tech. rep.

Goodman, Laurie S, Roger Ashworth, Brian Landy, and Ke Yin. 2010. "Negative Equity Trumps Unemployment in Predicting Defaults." *The Journal of Fixed Income* 19 (4):67–72.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2010. "The determinants of attitudes towards strategic default on mortgages." *Journal of Finance* Forthcoming.

Gyourko, Joseph and Joseph Tracy. 2014. "Reconciling theory and empirics on the role of unemployment in mortgage default." *Journal of Urban Economics* 80:87–96.

Haughwout, Andrew, Richard Peach, and Joseph Tracy. 2008. "Juvenile delinquent mortgages: bad credit or bad economy?" *Journal of Urban Economics* 64 (2):246–257.

Hedlund, A. 2011. "Illiquidity and Foreclosures in a Directed Search Model of the Housing Market." Available at SSRN 1932908.

Herkenhoff, K.F. 2013. "The Impact of Consumer Credit Access on Unemployment." Manuscript.

Herkenhoff, K.F. and L.E. Ohanian. 2012. "Foreclosure Delay and US unemployment." Federal Reserve Bank of St. Louis Working Paper 2012-017A.

Inspector General, Federal Housing Finance Agency Office of. 2012. "FHFAs Oversight of the Enterprises Efforts to Recover Losses from Foreclosure Sales." *Audit Report: AUD-2013-001* .

Kau, James B and Donald Keenan. 1995. "An Overview of the Option-Theoretic Pricing of Mortgages." *Journal of Housing Research* 6 (2):217–244.

Kau, James B, Donald Keenan, and Taewon Kim. 1993. "Transaction Costs, Suboptimal Termination and Default Probabilities." *Real Estate Economics* 21 (3):247–263.

Keys, Benjamin, Tomasz Piskorski, Amit Seru, and Vikrant Vig. 2012. "Mortgage financing in the housing boom and bust." 2. Chapter in *NBER Book Housing and the Financial Crisis*, Edward Glaeser and Todd Sinai, editors.

Laufer, Steven. 2012. "Equity Extraction and Mortgage Default." Tech. rep., Working Paper. New York University.

Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta. 2014. "Mortgage Modification and Strategic Behavior: Evidence from a Legal Settlement with Countrywide." *American Economic Review* 104 (9):2830–2857.

Mayer, Christopher, Karen Pence, and Shane M Sherlund. 2009. "The rise in mortgage defaults." *Journal of Economic Perspectives* 23 (1):27–50.

Mian, Atif and Amir Sufi. 2009. "The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis." *The Quarterly Journal of Economics* 124 (4):1449–1496.

Mocetti, Sauro and Eliana Viviano. 2013. "Looking behind mortgage delinquencies." Banca d'Italia, mimeo.

Pennington-Cross, Anthony. 2006. "The value of foreclosed property." *Journal of Real Estate Research* 28 (2):193–214.

Schelkle, Thomas. 2011. "Mortgage Default during the US Mortgage Crisis." Working paper, London School of Economics.

Schwartz, Eduardo S and Walter N Torous. 1989. "Prepayment and the Valuation of Mortgage-Backed Securities." *The Journal of Finance* 44 (2):375–392.

Stanton, Richard and Nancy Wallace. 1998. "Mortgage choice: what's the point?" *Real Estate Economics* 26 (2):173–205.

Vandell, Kerry D. 1995. "How ruthless is mortgage default? A review and synthesis of the evidence." *Journal of Housing Research* 6 (2):245–264.

Table 1: PSID vs. American Housing Survey

	PSID (2009-2011)	AHS (2011)
	Medians	
Principal Remaining ($)	120,000	120,000
Monthly Mortgage Payment ($)	1,100	1,015
Mortgage Interest Rate	5.0	5.3
Mortgage Term Remaining (Years)	24	22
LTV Ratio	0.71	0.71
	Fraction with	
Second Mortgage	0.18	0.13
ARM	0.09	0.07

Notes: AHS 2011 National Statistics taken from Table C-14A-OO. PSID Sample: Heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Defaulting households are dropped after default to avoid double counting.

Table 2: Summary Statistics for All PSID Households Heads in Sample, 2009-2011

(A) Demographics

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Age	44.08	30	44	58	43.19	31	42.5	57
Male (d)	0.85	0	1	1	0.68	0	1	1
Married (d)	0.74	0	1	1	0.55	0	1	1
Less than High School (d)	0.08	0	0	0	0.14	0	0	1
High School Education (d)	0.26	0	0	1	0.33	0	0	1
Some College Education (d)	0.27	0	0	1	0.29	0	0	1
College Grad+ Education (d)	0.33	0	0	1	0.17	0	0	1
Number of Children	1.01	0.0	1.0	3.0	1.23	0.00	1.00	3.00
Income	110,000	38,000	87,000	180,000	64,000	21,000	55,000	120,000

(B) Mortgage Characteristics

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Home value	240,000	80,000	180,000	450,000	190,000	50,000	140,000	350,000
Principal Remaining	150,000	35,000	120,000	290,000	180,000	31,000	130,000	350,000
Monthly Mortgage Payment	1253	500	1100	2200	1349	459	1100	2528
Second Mortgage (d)	0.18	0	0	1	0.21	0	0	1
Refinanced Mortgage (d)	0.46	0	0	1	0.40	0	0	1
ARM (d)	0.09	0	0	0	0.22	0	0	1
Mortgage Interest Rate	5.15	4	5	7	5.81	0	6	9
Mortgage Term Remaining	20.56	7	24	29	23.10	10	25	30
Recourse (d)	0.24	0	0	1	0.26	0	0	1
Judicial (d)	0.39	0	0	1	0.38	0	0	1
Default (60+ Days Late) (d)	0.04	0	0	0				
Months Delinquent	0.20	0	0	0	4.95	2	3	11.5
Loan to Value Ratio	0.71	0.28	0.71	1.04	1.01	0.52	0.94	1.66

(C) Employment

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Unemployed Head Last Year (d)	0.08	0	0	0	0.23	0	0	1
Unemployed Spouse Last Year (d)	0.05	0	0	0	0.12	0	0	1
Unemployed Head or Spouse Last Year (d)	0.13	0	0	1	0.31	0	0	1
Head Unemployed as of Survey Date (d)	0.06	0	0	0	0.21	0	0	1
Spouse Unemployed as of Survey Date (d)	0.04	0	0	0	0.10	0	0	1
Unemployment Duration	0.26	0	0	0	0.97	0	0	3
Unemployment Duration, Spouse	0.20	0	0	0	0.52	0	0	0

(D) Wealth

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Value of Stocks	21,000	0	0	25,000	2,655	0	0	0
Value of Liquid Assets	20,000	0	5,000	45,000	3,238	0	250	5,000
Unsecured Debt	16,000	0	4,354	40,000	18,000	0	6,750	40,000
Value of Vehicles	19,000	2,000	12,000	40,000	11,000	0	8,000	27,000
Value of Bonds	13,000	0	0	6,800	14,000	0	0	0
Business Income	41,000	0	0	0	4,973	0	0	0
Value of IRA	33,000	0	0	90,000	1,870	0	0	0
Value of Other Housing	29,000	0	0	30,000	3,794	0	0	0
N	5281				N	190		

Notes: Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Defaulting households are dropped after default to avoid double counting. Pooled averages and pooled distributions reported above. Liquid assets include checking and savings account balances, money market funds, certificates of deposit, Treasury securities, and other government saving bonds. (d) indicates a dummy variable.

Table 3: Summary of Shocks and Default Rates

Panel A: Default Rates Among Subgroups of Households								
	Unemployed?		Negative Equity?		Low Liquid Assets?		Income Drop of 50 percent or More?	
	Yes	No	Yes	No	Yes	No	Yes	No
Default Rate	10.1 %	3.0 %	11.3 %	2.4%	10.1%	1.6%	10.7%	3.3%
# of HHs in Subgroup	435	4846	708	4573	1256	4025	233	5048
	Recently Divorced?		Cash Flow Shock?		Any Non-Equity Shock?		High Hospital Bills?	
	Yes	No	Yes	No	Yes	No	Yes	No
Default Rate	9.7%	3.5%	8.9%	2.5%	5.4%	1.2%	7.0%	3.6%
# of HHs in Subgroup	113	5168	919	4362	3031	2250	57	5224

Panel B: Among Defaulters/Non-Defaulters, How Many Had Shocks?								
	Unemployed?		Negative Equity?		Low Liquid Assets?		Income Drop of 50% or More?	
	Defaulters	Nondefaulters	Defaulters	Nondefaulters	Defaulters	Nondefaulters	Defaulters	Nondefaulters
Fraction HHs w/ shock	23.2%	7.7%	42.1%	12.3%	66.8%	22.2%	13.2%	4.1%
# of HHs in Subgroup	190	5091	190	5091	190	5091	190	5091
	Recently Divorced?		Cash Flow Shock?		Any Non-Equity Shock?		High Hospital Bills?	
	Defaulters	Nondefaulters	Defaulters	Nondefaulters	Defaulters	Nondefaulters	Defaulters	Nondefaulters
Fraction HHs w/ shock	5.8%	2.0%	43.2%	16.4%	86.3%	56.3%	2.1%	1.0%
# of HHs in Subgroup	190	5091	190	5091	190	5091	190	5091

Notes: Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Cash flow shock includes recent divorce, unemployed head or spouse, or severe income loss of 50 percent or more. Any non-equity shock includes recent divorce, unemployment of head or spouse, a 50 percent reduction of income, low liquid assets, high hospital bills, or high medical bills. Subgroups of households defined in text, and all other shocks defined in text.

Table 4: Baseline Results: Linear Probability Model.

	Dependent Variable: 60+ Days Delinquent Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
LTV	0.096***	0.094***	0.087***	0.077***	0.096***	0.030
	(8.43)	(6.73)	(6.32)	(5.48)	(6.87)	(0.56)
Unemployed (d)	0.068***	0.053***	0.049***	-0.022		
	(4.75)	(3.71)	(3.52)	(-0.74)		
Spouse Unemployed (d)	0.036**	0.040**	0.034**	0.035**		
	(2.19)	(2.47)	(2.13)	(2.18)		
Low Liquid Assets (d)			0.053***	0.053***		
			(6.45)	(6.40)		
High Hospital Bills (d)			0.045	0.043		
			(1.41)	(1.35)		
High Medical Bills (d)			0.005	0.004		
			(0.84)	(0.79)		
Divorce (d)			0.033	0.033		
			(1.19)	(1.19)		
High Unsecured Debt (d)			0.003	0.003		
			(0.21)	(0.25)		
LTV * Unemployed (d)				0.100**		
				(2.10)		
State UR					-0.000	-0.005
					(-0.05)	(-1.28)
State UR * LTV						0.007
						(1.17)
Demographic Controls	N	Y	Y	Y	Y	Y
Mortgage Controls	N	Y	Y	Y	Y	Y
State Controls	N	Y	Y	Y	Y	Y
# Households	5,281	5,281	5,281	5,281	5,268	5,268
R^2	0.043	0.083	0.097	0.100	0.074	0.075

Notes: Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. (d) indicates a dummy variable.

Table 5: Baseline Results: Logit Model.

Dependent Variable: 60+ Days Delinquent Indicator	(1)	(2)	(3)	(4)
LTV	0.068***	0.053***	0.052***	0.024***
	(9.63)	(7.59)	(10.83)	(6.66)
Unemployed (d)	0.063***	0.026***	0.054***	0.013***
	(4.57)	(4.00)	(4.32)	(4.18)
Spouse Unemployed (d)	0.026**	0.025***	0.021*	0.011***
	(1.99)	(2.96)	(1.91)	(2.84)
Low Liquid Assets (d)		0.039***		0.017***
		(6.91)		(6.46)
High Hospital Bills (d)		0.042**		0.018**
		(2.30)		(2.29)
High Medical Bills (d)		0.001		0.000
		(0.10)		(0.10)
Divorce (d)		0.022**		0.010**
		(2.00)		(2.00)
High Unsecured Debt (d)		0.005		0.002
		(0.51)		(0.51)
LTV * Unemployed (d)		0.023		0.022
		(0.89)		(1.52)
Demographic Controls	N	Y	N	Y
Mortgage Controls	N	Y	N	Y
State Controls	N	Y	N	Y
# Households	5,268	5,268	5,268	5,268

Notes: Columns (1) and (2) report average marginal effects (AMEs), while columns (3) and (4) report marginal effects at the mean (MEMs). Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. (d) indicates a dummy variable.

Table 6: Robustness Checks, Linear Probability Model. Cols. (1) and (2) control for involuntary job loss. Cols. (3) and (4) control for prior unemployment spells. Cols. (5) and (6) control for forward house price growth. Cols. (7) and (8) control for lagged house price growth.

	Invol. Sep.		Prior Unempl.		Forward HP		Lagged HP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LTV	0.088***	0.086***	0.087***	0.076***	0.071***	0.067***	0.084***	0.071***
	(6.43)	(6.17)	(6.27)	(5.43)	(3.32)	(3.05)	(5.75)	(4.83)
Involuntarily Separated (d)	0.047**	0.005						
	(2.45)	(0.12)						
LTV *Involuntarily Separated (d)		0.060						
		(0.90)						
Involuntarily Separated Spouse (d)	0.055	0.056*						
	(1.64)	(1.69)						
Unemployed (d)			0.048***	-0.024	0.059***	0.029	0.058***	-0.038
			(3.48)	(-0.80)	(2.61)	(0.59)	(3.79)	(-1.12)
LTV * Unemployed (d)				0.101**		0.043		0.138**
				(2.13)		(0.55)		(2.47)
Spouse Unemployed (d)			0.034**	0.035**	0.050*	0.052*	0.036**	0.036**
			(2.11)	(2.16)	(1.81)	(1.89)	(2.03)	(2.04)
Low Liquid Assets (d)	0.056***	0.056***	0.054***	0.053***	0.040***	0.040***	0.049***	0.048***
	(6.66)	(6.64)	(6.50)	(6.44)	(3.09)	(3.09)	(5.44)	(5.38)
High Hospital Bills (d)	0.045	0.044	0.045	0.043	-0.021	-0.021	0.055	0.052
	(1.39)	(1.38)	(1.39)	(1.32)	(-1.39)	(-1.46)	(1.53)	(1.45)
High Medical Bills (d)	0.005	0.006	0.004	0.004	0.004	0.004	0.012*	0.011*
	(1.00)	(1.02)	(0.75)	(0.69)	(0.49)	(0.50)	(1.93)	(1.85)
Divorce (d)	0.034	0.033	0.034	0.034	0.007	0.006	0.056	0.055
	(1.21)	(1.20)	(1.21)	(1.21)	(0.23)	(0.21)	(1.21)	(1.19)
High Unsecured Debt (d)	0.003	0.004	0.003	0.004	0.015	0.015	-0.009	-0.009
	(0.27)	(0.32)	(0.25)	(0.30)	(0.69)	(0.69)	(-0.77)	(-0.74)
Lagged House Price Growth							0.002	0.002
							(0.36)	(0.44)
Forward House Price Growth					-0.000	0.000		
					(-0.00)	(0.02)		
1 Prior Unemployment Spell (d)			0.001	0.001				
			(0.11)	(0.11)				
2 Prior Unemployment Spells (d)			0.048*	0.049**				
			(1.95)	(2.00)				
3 Prior Unemployment Spells (d)			-0.046	-0.045				
			(-1.62)	(-1.56)				
4 Prior Unemployment Spells (d)			-0.009	-0.007				
			(-0.20)	(-0.16)				
5 Prior Unemployment Spells (d)			-0.077***	-0.079***				
			(-3.45)	(-3.69)				
7 Prior Unemployment Spells (d)			0.123	0.124				
			(0.58)	(0.58)				
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Mortgage Controls	Y	Y	Y	Y	Y	Y	Y	Y
State Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,281	5,281	5,281	5,281	2,151	2,151	4,310	4,310
R-squared	0.094	0.094	0.100	0.102	0.094	0.094	0.100	0.105

Notes: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Involuntary job loss includes, plant closures, strike/lockout, and layoff. Forward and lagged house price growth defined as percentage change in self-reported home value. Dummies for prior unemployment include all types of unemployment spells from 1994-2005. (d) indicates a dummy variable.

Table 7: Impact of Cash Flow Shocks, Non-Equity Shocks, and Income Loss on the Propensity to Default. Cols. (1) and (2) illustrate the impact of cash flow shocks (unemployment of head or spouse, divorce, or 50 percent income loss) on default, Cols. (3) and (4) illustrate the impact of any non-equity shock on default, and Cols. (5) (6) illustrate the impact of a 50 percent income loss on default.

	(1)	(2)	(3)	(4)	(5)	(6)
LTV	0.093***	0.073***	0.094***	0.049***	0.096***	0.094***
	(6.71)	(5.23)	(6.78)	(3.22)	(6.90)	(6.70)
Cash Flow Shock (d)	0.052***	-0.019				
	(5.49)	(-0.82)				
Cash Flow Shock (d) * LTV		0.096***				
		(2.83)				
Any Non-Equity Shock (d)			0.025***	-0.024*		
			(5.70)	(-1.88)		
Any Non-Equity Shock (d) * LTV				0.069***		
				(3.41)		
Income<50% (d)					0.069***	0.031
					(3.53)	(0.70)
Income<50% (d) * LTV						0.055
						(0.82)
Demographic Controls	Y	Y	Y	Y	Y	Y
Mortgage Controls	Y	Y	Y	Y	Y	Y
State Controls	Y	Y	Y	Y	Y	Y
Observations	5,281	5,281	5,281	5,281	5,281	5,281
R-squared	0.085	0.090	0.078	0.082	0.080	0.081

Notes: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Cash flow shock includes recent divorce, unemployed head or spouse, or severe income loss of 50 percent or more. Any non-equity shock includes recent divorce, unemployment of head or spouse, a 50 percent reduction of income, low liquid assets, high hospital bills, or high medical bills. (d) indicates a dummy variable.

Table 8: Summary Statistics for "Can Pay"/"Can't Pay" households.

(A) Demographics

	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
White (d)	0.81	1	0.35	0	0.55	1	0.49	0
Black (d)	0.14	0	0.53	1	0.34	0	0.32	0
Age	46.05	47	44.06	44	44.72	46	43.46	42
Male (d)	0.89	1	0.77	1	0.76	1	0.68	1
Married (d)	0.81	1	0.59	1	0.62	1	0.57	1
Less than High School (d)	0.04	0	0.00	0	0.18	0	0.14	0
High School Education (d)	0.20	0	0.18	0	0.37	0	0.43	0
Some College Education (d)	0.24	0	0.47	0	0.19	0	0.16	0
College Grad+ Education (d)	0.52	1	0.35	0	0.23	0	0.27	0
Number of Children	0.90	0	1.18	1	1.03	1	1.00	0
Income ($)	140,000	110,000	91,000	68,000	64,000	58,000	44,000	37,000

(B) Mortgage Characteristics

	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Home value ($)	310,000	240,000	260,000	200,000	160,000	130,000	200,000	130,000
Principal Remaining ($)	160,000	130,000	280,000	240,000	110,000	90,000	160,000	110,000
Monthly Mortgage Payment ($)	1,375	1,200	1,907	1,850	966	800	1,258	1,100
Second Mortgage (d)	0.18	0	0.35	0	0.17	0	0.22	0
Refinanced Mortgage (d)	0.53	1	0.41	0	0.37	0	0.32	0
ARM (d)	0.07	0	0.24	0	0.12	0	0.24	0
Mortgage Interest Rate (%)	4.89	5	4.53	6	5.68	6	5.03	5
Mortgage Term Remaining	19.06	20	25.18	25	20.44	23	22.92	24
Recourse (d)	0.25	0	0.24	0	0.22	0	0.22	0
Judicial (d)	0.40	0	0.47	0	0.42	0	0.54	1
Default (60+ Days Late) (d)	0.01	0	1.00	1	0.19	0	1.00	1
Months Delinquent	0.04	0	4.65	3	1.13	0	5.57	4
Loan to Value Ratio	0.62	0.612	1.25	1.019	0.80	0.787	0.93	0.878

(C) **Employment**

	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Unemployed Head Last Year (d)	0.02	0	0.00	0	1.00	1	1.00	1
Unemployed Spouse Last Year (d)	0.04	0	0.12	0	0.12	0	0.22	0
Unemployed Head or Spouse Last Year (d)	0.06	0	0.12	0	1.00	1	1.00	1
Head Unemployed as of Survey Date (d)	0.00	0	0.00	0	1.00	1	1.00	1
Spouse Unemployed as of Survey Date (d)	0.03	0	0.00	0	0.12	0	0.22	0

(D) Wealth

	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Value of Stocks ($)	51,000	0	29000	0	212	0	108.11	0
Value of Liquid Assets ($)	42,000	20,000	21,000	4,000	2,615	500	648	0
Unsecured Debt ($)	6,720	400	25,000	16,000	28,000	9,953	29,000	5,000
Value of Vehicles ($)	24,000	18,000	17,000	20,000	11,000	7,250	8,156	8,000
Value of Bonds ($)	33,000	0	160,000	25,000	482	0	270	0
Value of Business ($)	81,000	0	1,875	0	11,000	0	56	0
Value of IRA ($)	59,000	0	15,000	0	14,000	0	0	0
N		2126		17		193		37

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Can Pay: Head employed with at least six months worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. "Can't pay": Head is unemployed and has less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. "Won't Pay": "Can pay" borrowers who default. "Don't Pay": "Can't pay" borrowers who default. (d) indicates a dummy variable.

Table 9: Alternate Definitions of "Can Pay" and "Can't Pay"

	Can Pay	**Can't Pay**
Default Rate, Baseline Definition	0.80%	19.20%
N	2126	193
Default Rate, Baseline Definition w/ Negative Equity (CLTV$\geq$1)	5.20%	33.30%
N	174	39
Default Rate, Baseline Definition w/ CLTV$\geq$.9	3.80%	28.10%
N	341	64
Default Rate, Alternate Definition	1.70%	26.60%
N	2906	94
Default Rate, Alternate Definition w/ Negative Equity (CLTV$\geq$1)	6.00%	30.40%
N	349	23
Default Rate, Alternate Definition w/ CLTV$\geq$.9	3.80%	24.20%
N	732	33

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Baseline Definition of "Can Pay": Head employed with at least six months worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Baseline Definition of "Can't Pay": Head is unemployed and has less than 1 month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. "Baseline Definition w/ Negative Equity" imposes additional restriction that Combined Loan to Value (CLTV) is greater than or equal to 1. Alternate Definition of "Can Pay": includes all households who have had no unemployment spells and have one of either (i) at least 6 months worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt or (ii) a debt-to-income ratio$<$ 31 percent. Alternate Definition of "Can't Pay": households have both (i) an unemployed head and a non-employed spouse and (ii) has less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. "Alternate Definition w/ Negative Equity" imposes additional restriction that Combined Loan to Value (CLTV) is greater than or equal to 1.

Table 10: Sensitivity of “Can’t Pay” and “Can Pay” Households to Home Equity

	(1)	(2)	(3)	(4)
	Can’t Pay	Can’t Pay	Can Pay	Can Pay
LTV	0.123*	0.100	0.049***	0.049***
	(1.86)	(1.43)	(3.13)	(3.19)
Demographic Controls	Y	Y	Y	Y
State Controls	N	Y	N	Y
Observations	193	193	2,126	2,126
R-squared	0.122	0.162	0.063	0.069

Notes: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. “Can Pay”: Head employed with at least six months worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. “Can’t pay”: Head is unemployed and has less than one month’s worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt.

Table 11: Wealth Distribution of Defaulters with Negative Home Equity.

Panel A: Defaulters with LTV>1, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	1.24	0.00	0.00	0.28	1.26	3.33	2.81	78
Illiquid Assets to Mortgage Payment Ratio	15.72	0.00	2.50	6.44	16.15	31.29	34.03	80
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	7.48	-12.96	-2.27	2.99	10.57	22.87	39.04	78
Liquid + Stocks and Bonds to Mortgage Payment Ratio	7.87	0.00	0.00	0.44	1.76	4.55	34.15	78

Panel B: Defaulters with LTV>1, Weighted, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	1.46	0.00	0.00	0.64	1.82	4.02	3.06	78
Illiquid Assets to Mortgage Payment Ratio	14.14	0.00	1.34	4.80	15.63	30.06	30.45	80
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	6.37	-11.81	-2.04	2.50	10.75	20.86	34.01	78
Liquid + Stocks and Bonds to Mortgage Payment Ratio	6.45	0.00	0.01	0.68	1.84	4.05	29.34	78

Panel C: All Defaulters, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	2.21	0.00	0.00	0.22	1.28	3.81	13.56	186
Illiquid Assets to Mortgage Payment Ratio	23.62	0.00	2.94	7.70	18.18	38.16	56.68	190
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	12.40	-27.06	-3.86	3.57	13.51	36.44	62.16	186
Liquid + Stocks and Bonds to Mortgage Payment Ratio	9.23	0.00	0.00	0.29	1.76	5.00	38.88	186

Panel D: All Defaulters, Weighted, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	4.00	0.00	0.00	0.37	1.62	4.00	21.78	186
Illiquid Assets to Mortgage Payment Ratio	25.38	0.00	2.50	6.37	17.23	35.79	64.72	190
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	17.74	-19.87	-3.13	3.67	12.92	46.32	71.00	186
Liquid + Stocks and Bonds to Mortgage Payment Ratio	11.11	0.00	0.01	0.47	1.98	4.55	40.62	186

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Liquid assets include checking and savings account balances, money market funds, certificates of deposit, Treasury securities, and other government saving bonds. Illiquid assets include stocks, bonds, vehicles, business income, and retirement income. Assets are expressed as a ratio of the monthly mortgage payment.

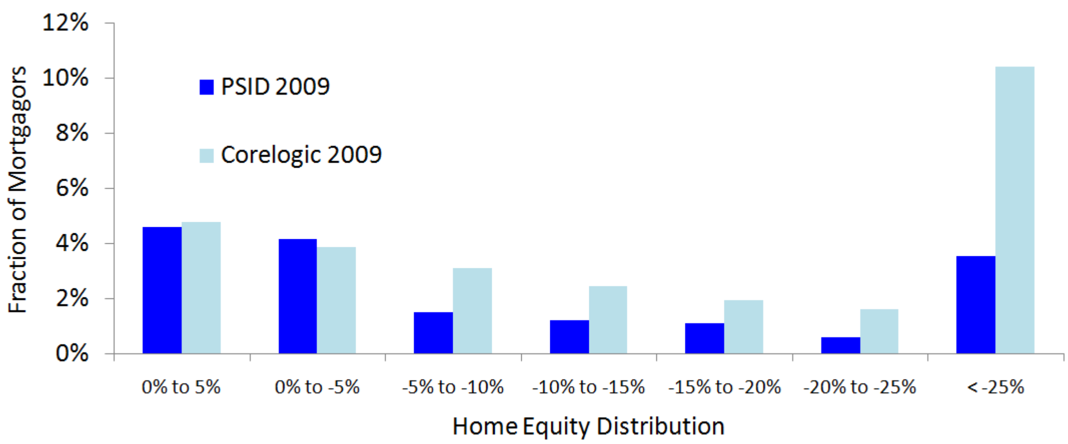
Table 12: Wealth Distribution of Nondefaulters.

	Nondefaulters, 2009-2011							
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**	**sd**	**N**
Liquid Assets to Mortgage Payment Ratio	21.58	0.00	1.20	4.55	13.89	37.41	290.62	4919
Illiquid Assets to Mortgage Payment Ratio	296.54	2.47	7.94	21.27	66.12	220.00	9963.94	5090
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	185.65	-14.75	3.06	22.39	78.45	253.03	5341.97	4919
Liquid + Stocks and Bonds to Mortgage Payment Ratio	46.77	0.00	1.56	6.72	25.64	90.63	324.39	4919

	Nondefaulters, Weighted, 2009-2011							
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**	**sd**	**N**
Liquid Assets to Mortgage Payment Ratio	22.45	0.00	1.54	5.52	16.67	43.10	211.92	4919
Illiquid Assets to Mortgage Payment Ratio	272.62	2.75	8.51	24.38	87.50	283.33	8414.80	5090
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	222.48	-11.53	5.00	27.80	105.88	320.63	5910.51	4919
Liquid + Stocks and Bonds to Mortgage Payment Ratio	55.51	0.14	2.12	8.54	33.33	119.05	277.71	4919

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Liquid assets include checking and savings account balances, money market funds, certificates of deposit, Treasury securities, and other government saving bonds. Illiquid assets include stocks, bonds, vehicles, business income, and retirement income. Assets are expressed as a ratio of the monthly mortgage payment.

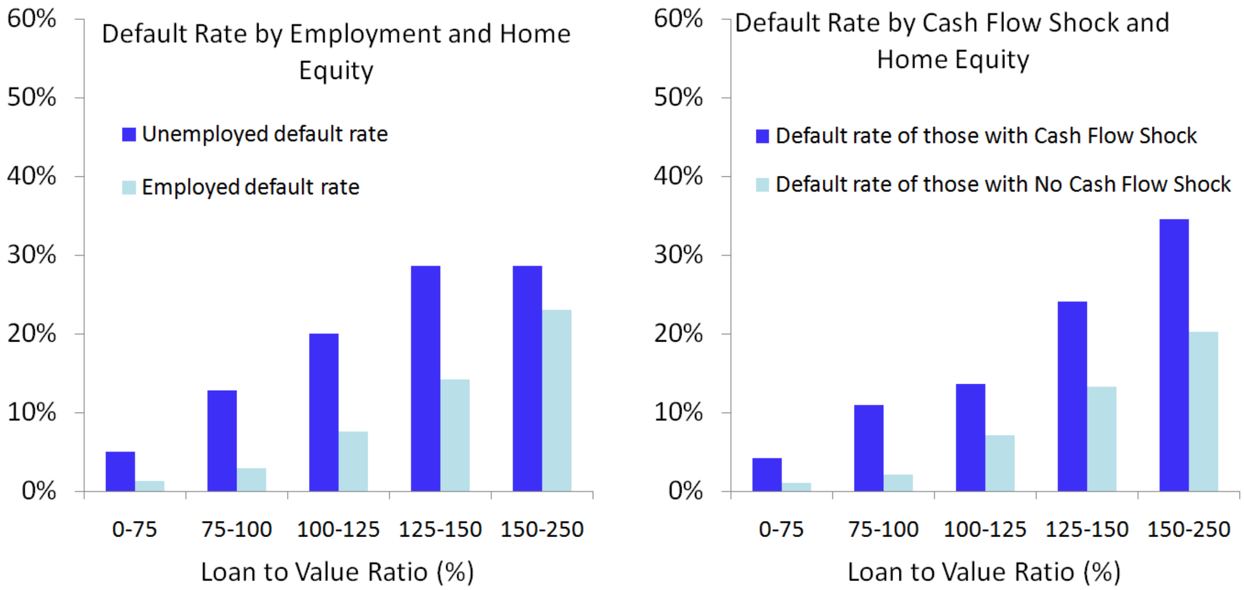
Figure 1. Home Equity Distribution.



Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. CoreLogic data taken as of 2009, "First American CoreLogic Releases Q3 Negative Equity Data," available from `http://www.recharts.com/reports/FACLNERQ32009/FACLNERQ32009.pdf`

Figure 2. Default Rate by Shocks and Home Equity. Fraction of Defaulters/Nondefaulters with Shocks by Home Equity.

Panel A **Panel B**



Notes: Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Cash flow shock includes recent divorce, unemployed head or spouse, or severe income loss of 50 percent or more. Unemployed includes both those unemployed last year and as of the survey date.

Figure 3. Definition of Types of Defaults.

	Did Pay	**Didn't Pay**
Can Pay	**(1) Repayment**	**(2) Type I Error "Won't Pay" Strategic Default**
Can't Pay	**(3) Type II Error "Will Pay"**	**(4) "Normal" Non-Strategic Default**

ONLINE APPENDIX

A.1. Model

In this section, we lay out a model that nests the three paradigms discussed in the main body of the text: (1) the frictionless option theoretic model (2) the double trigger model, and (3) the portfolio constraints model. We lay out the assumptions necessary for each model and illustrate how default policy functions behave under each set of assumptions. Lastly, we compare predicted default behavior with the PSID.

Let $t = 0, 1$ index time. There is a continuum of households that discount the future at rate β and have twice continuously differentiable, increasing, and concave preferences over nondurable consumption (c_t). Households differ at date 0 with respect to their beliefs over the state of the world at date 1. In the example below, we assume there are two possible states of the world at date 1, *high* and *low*, and that households believe with probability p_L that the state of the world will be *low*. The distribution of beliefs among households is summarized by the cumulative distribution function $G(p_L)$. Let $\theta \in \{H, L\}$ denote the realization of the state of the world and let π_θ be the true probability of transitioning to state θ in period 1.

With the exception of beliefs over the state of the world at date 1, each household is initially endowed with an identical state vector at date 0. All households have a mortgage that has remaining principal given by x_0 and required mortgage payment given by m_0. Initial house prices (P_0), the savings rate (r_s), the borrowing rate (r_b), initial income (y_0), and initial wealth (w_0) are also taken as given. At date 1, we assume that both house prices, $P_1(\theta)$, and income, $y_1(\theta)$, are functions of the state of the world. We assume that in the *high* state of the world, both income and house prices are strictly greater than in the *low* state of the world ($P_1(H) > P_1(L)$ and $y_1(H) > y_1(L)$). Given beliefs over the aggregate state of the world, households make choices to maximize their preferences given below:

$$u(c_0) + \beta \mathbb{E}_\theta[u(c_1)].$$

To simplify matters, we assume that $P_0 < x_0$, which means that all borrowers have negative equity in the initial period. A borrower in our model faces two different budget constraints: The first obtains when the borrower defaults and the other obtains when the borrower makes the mortgage payment. By deciding whether or not to make the mortgage payment, the borrower implicitly chooses the budget constraint that yields higher lifetime utility.

We assume that, after default, the household rents an exactly equivalent house. Such an assumption is somewhat unrealistic, but simplifies the exposition significantly since it means that housing consumption need not appear in the utility function. Without loss of generality, we then define the mortgage payment m_0 as net of rent for the house. In other words, if the mortgage payment is \$1500 and an identical house rents for \$1000 then we define $m_0 = \$500$.

We assume that after default the household can enter into any possible financial contract including buying the same house back with a new mortgage. We assume absence of arbitrage, which implies that if a household does buy a house without paying any money up front, then the value of future cash flows from the house must be zero. We return to this point later. In addition, we assume that the household can hedge its position in the house by taking a position γP_0 in residential real estate. In general, we restrict $\gamma = 0$, but an unrestricted γ is crucial to a whole class of models.

If the household makes the mortgage payment, the budget constraint is:

$$c_0 + s - b + \gamma P_0 \leq y_0 + w - m_0 \tag{4}$$
$$c_1(\theta) \leq y_1(\theta) - b(1 + r_b) + s(1 + r_s) + \max\{P_1(\theta) - X_1, 0\} + \gamma P_1(\theta) \tag{5}$$
$$0 \leq b \leq \overline{b} \tag{6}$$
$$0 \leq s \tag{7}$$
$$\underline{\gamma} \leq \gamma \leq \overline{\gamma}, \tag{8}$$

where equation (3) corresponds to a constraint on the amount that the household can borrow, $\overline{b}$; equation (4) means that households cannot save at the borrowing rate, r_b; and equation (5) limits the ability of the household to hedge its real estate position.

If the household chooses not to make the mortgage payment, then it is faced with a slightly different budget constraint:[21]

$$c_0 + s - b + \gamma P_0 \leq y_0 + w + \max\{P_0 - X_0, 0\} \tag{9}$$
$$c_1(\theta) \leq y_1(\theta) + s(1 + r_s) - b(1 + r_b) + \gamma P_1(\theta) \tag{10}$$
$$0 \leq b \leq \overline{b} \tag{11}$$
$$0 \leq s \tag{12}$$
$$\underline{\gamma} \leq \gamma \leq \overline{\gamma}. \tag{13}$$

[21] For simplicity, we assume there is no recourse in the model. See Herkenhoff and Ohanian (2012) and Inspector General (2012) for more on the pursuit of deficiencies. The FHFA reports 298,327 foreclosures with only 35,231 of those foreclosures being pursued for a deficiency, and recovery rate of less than 0.25 percent.

With the assumption that there is negative equity in the initial period, equation 9 reduces to,

$$c_0 + s - b + \gamma P_0 \leq y_0 + w. \tag{14}$$

Our model abstracts from many features of the default decision. For example, a household that suffers an income loss might want to change the level of its housing consumption, a possibility that we assume away in our model. But the value of the model is that it encompasses most of the popular theories of why borrowers default. Specifically, we show now that with one set of assumptions, our model is: (1) the frictionless option model of Epperson et al. (1985); (2) a model of purely liquidity-driven default, as in Bhutta, Dokko, and Shan (2011); and (3) a model of portfolio choice with liquidity constraints similar to Campbell and Cocco (2011), Laufer (2012), and Schelkle (2011).

A.1.1. Frictionless Model

Suppose that all households have correct beliefs about the state of the world in period 1 (that is, for every household $p_L = \pi_L$). Suppose further that $r_b = r_s = r$ and $\overline{b} = \infty$ and that $\overline{\gamma} = -\underline{\gamma} = \infty$. Let ϕ_i be the price of an Arrow-Debreu security paying \$1 in state i. In that case, it is easy to show that the budget constraint for mortgage payers (equations (4)–(8)) collapse into a single equation:

$$c_0 + \phi_L c_1(L) + \phi_H c_1(H) = y_0 + \phi_L y_1(L) + \phi_H y_1(H) + w - m_0 + \sum_{\theta \in \{H,L\}} \phi_\theta \max\bigl(P_1(\theta) - X_1, 0\bigr). \tag{15}$$

The budget constraint for defaulters (equations (10)–(13) and equation (14) can be similarly re-written as:

$$c_0 + \phi_L c_1(L) + \phi_H c_1(H) = y_0 + \phi_L y_1(L) + \phi_H y_1(H) + w. \tag{16}$$

Based on the above, we can state the following proposition:

Proposition 1 *Suppose*

1. $\overline{\gamma} = -\underline{\gamma} = \infty$.
2. $r_b = r_s = r$ *and* $\overline{b} = \infty$.

If $P_0 < X_0$, then default occurs if and only if

$$m_0 > \sum_{\theta \in \{H,L\}} \phi_\theta \max\bigl(P_1(\theta) - X_1, 0\bigr). \tag{17}$$

The proof of the proposition involves subtracting equation (16) (the budget from not defaulting) from equation (15) (the budget from defaulting). Whenever there are more resources available to the household from defaulting, in net present value, the household will default. This occurs precisely when the mortgage payment is larger than the next expected payoff from holding the house. In fact, equation (17) is the binomial analogue of the standard mortgage default condition in Epperson et al. (1985). The right-hand side of equation (17) is the value of a call option on the house with a strike price equal to the outstanding balance on the mortgage next period. The mortgage contract gives the borrower the right to buy that call for m_0, so if the value of the call exceeds the price, the borrower makes the payment, and if the value falls short, the borrower defaults.[22]

One may ask, at this point, why the household would ever choose to make the mortgage payment if it could default and buy another house with a mortgage with a lower strike price. The answer is that any new investment in a house must have zero net present value: the amount invested must equal the value of the contract. For example, if the household buys a house and puts no money down, then the value of all future cash flows must be zero. By contrast, if equation (17) is not satisfied, the value of future cash flows exceeds the amount paid. In other words, if condition (17) is not satisfied, defaulting and buying another house with a new mortgage *reduces* utility.

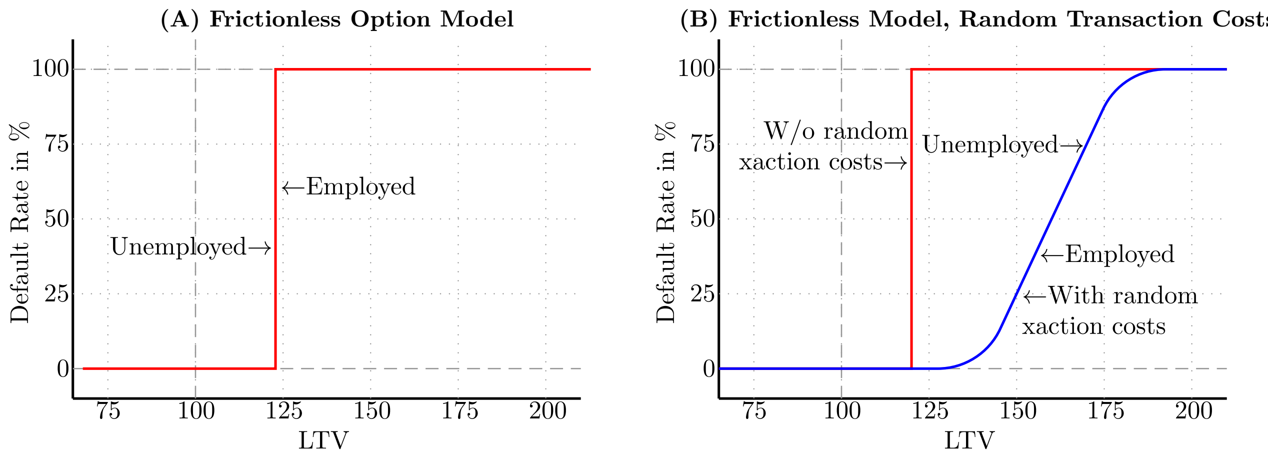
Panel (A) of Figure A.1 shows the optimal default rule as a function of the LTV ratio. Equation (17) implies that there is a unique critical level of LTV such that all borrowers who live in a given house with a given mortgage will default. The critical LTV ratio is independent of preferences and individual beliefs about the distribution of future house prices. But, more importantly for our purpose, the critical LTV is also independent of income or wealth or any other circumstances of the individual borrower.

Conditions 1 and 2 in Proposition 1 are strong, but they are crucial. Condition 2 ensures that the borrower's marginal utilities of date 1 consumption are proportional to the state prices, and Condition 1 ensures that the borrower's marginal rate of substitution equals the economy-wide marginal rate of transformation.

Researchers have long noted the disconnect between empirical patterns of default and the frictionless model's prediction that the LTV ratio is a sufficient statistic for determining

[22]By put-call parity, we can re-write condition (17) as $m_0 + \frac{1}{1+r} X_1 - \sum_\theta \bigl(X_1 \sum_\theta \bigl(X_1 - P_1(\theta)\bigr) > P_0$, which is the condition in Epperson et al. (1985) stating that default occurs when the value of the house falls short of the value of the mortgage, taking into account the value of the implied put option.

Figure A.1. The Frictionless Model with and without Transaction Costs.



default behavior.[23] In particular, while defaults are higher at higher LTVs, the relationship is smooth, not discontinuous, as predicted by the frictionless model. Researchers, notably Kau, Keenan, and Kim (1993) and Stanton and Wallace (1998), proposed to remedy this by introducing random transaction costs. The idea is that households face additional costs of defaulting (moving costs, costs of reduced availability of credit, etc.) that drive a wedge into equation (17), effectively reducing the costs of paying the mortgage. If the transaction costs are different across households, then the frictionless model implies that the relationship between default and LTV is smooth, as depicted in Panel (B) of Figure A.1. It is important, however, to stress that the model still implies that there should be no relationship between default and levels of income and wealth, unless there is a relationship between transaction costs and employment. While one could imagine reasons why transaction costs might be lower for unemployed households (unemployed households may need to move anyway), one could also imagine the opposite (unemployed households lack the money to pay moving costs).

A.1.2. The Double Trigger Model and Strategic Default

An alternative theory of default is the double trigger model, which is used by both Bajari, Chu, and Park (2008) and Bhutta, Dokko, and Shan (2011). In these double trigger models, if a household has negative equity, a liquidity shock *implies* default. There is no interaction between unemployment (a common liquidity shock) and the depth of negative equity. An unemployed household with an LTV ratio of 110 percent is just as likely to default as an

[23]For example, Vandell (1995).

unemployed household with an LTV ratio of 190 percent.

According to the double trigger paradigm, there are two types of default. Households that default in a nonstrategic manner satisfy two criteria: negative equity and the inability to afford the mortgage payment. In contrast, households that default in a strategic manner satisfy the first criterion (negative equity) but not the second criterion (they can afford the mortgage payment). For example, Experian and Oliver Wyman (2009) write that:

> We define "strategic default" as default behavior on a mortgage purely out of negative equity considerations; that is, the borrower has the ability to make monthly payments on his mortgage, but chooses not to do so.

In another prominent study of strategic default, Guiso, Sapienza, and Zingales (2010) measure the number of strategic defaults by conducting a survey and asking:

> Of the people you know who have defaulted on their mortgage, how many do you think walked away even if they could afford to pay the monthly mortgage?

Using our simple model we can determine a necessary and sufficient condition for this concept of strategic default. It is easier to start by considering what leads to nonstrategic default. Basically, if making the mortgage payment leads to negative consumption, then it makes sense to default. This logic yields another proposition.

Proposition 2 *Suppose that $\gamma = 0$ and the borrowing limit $\bar{b}$ is finite. A nonstrategic default occurs when:*

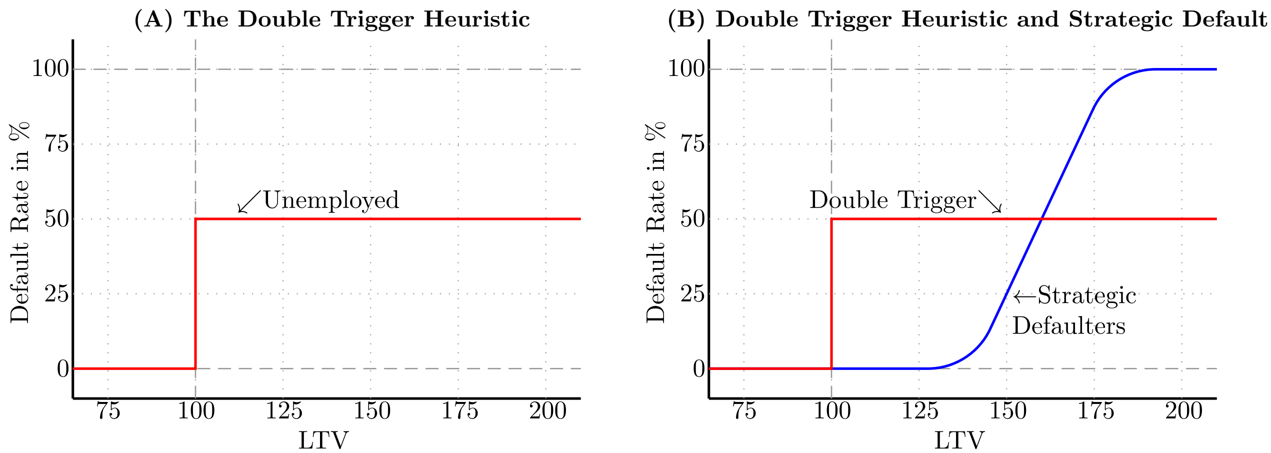
$$y_0 + w + \bar{b} < m_0. \tag{18}$$

Equation (18) is an extremely strong condition. A nonstrategic default occurs in this model if the household pools its assets, income, *and* borrowing capacity and still cannot make the mortgage payment. Conversely, a strategic default occurs when the household defaults despite having its pooled resources that exceed the monthly mortgage payment.

The key prediction of the double trigger model is that while negative equity is necessary for default, the level of equity is irrelevant. Unemployment generates an income loss, which for some fraction α of households, means that the household satisfies inequality (18). Panel (A) of Figure A.2 shows the relationship between default and the LTV ratio in the double trigger model: below an LTV ratio of 100 percent no one defaults, and above an LTV ratio of 100 percent some fraction α of unemployed borrowers default. What is crucial here is that α is independent of the LTV ratio. Going from an LTV ratio of 110 percent to 150 percent has no effect on default behavior.

As mentioned above, the double trigger model implicitly defines strategic default. A household that defaults but doesn't satisfy inequality (18) is a strategic defaulter. As a

Figure A.2. The Double Trigger Model and Strategic Default.



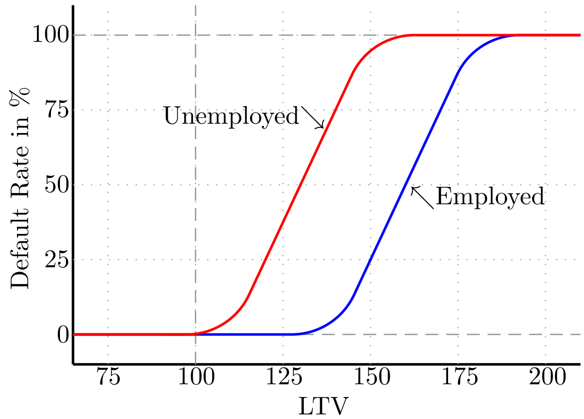
result, many researchers divided the world into two groups: strategic defaulters and double trigger defaulters. Panel (B) of Figure A.2 illustrates this view. Consider a pool of borrowers in which 40 percent are unemployed and half of the unemployed borrowers cannot afford their mortgages. According to the theory, 20 percent of borrowers are "double trigger defaulters" and the remaining 80 percent follow the frictionless model with transaction costs as depicted in Panel (B) of Figure A.1. The analytical approach of Bhutta, Dokko, and Shan (2011) essentially follows Panel (B) of Figure A.2. These authors assume that all defaults at 100 LTV are double trigger and that any increase in the default probability above 100 LTV (controlling for different characteristics of the loans above 100 LTV) are strategic defaults.

A.1.3. Portfolio Constraints

In this section, we relax the condition that $r_b = r_s$ and impose that $\gamma = 0$ and $\bar{b} < \infty$, to match the reality that households can neither take on unlimited amounts of unsecured debt nor can they typically take on *any* unsecured debt at the riskless rate. Similarly, not only can households not take unlimited short positions in residential real estate, they can't take any short positions at all and, worse, there are no tradable assets perfectly correlated with the value of a particular house. Figure A.3 provides a heuristic diagram of the default decision across employed and unemployed households in this framework. Unemployed households are more likely to default than employed households; however, for extreme levels of equity, there is no interaction.

Unlike the other frictionless and double trigger models, the portfolio-constrained model does not typically allow for analytical solutions so, instead, we consider numerical examples that illustrate the basic predictions of the model.

Figure A.3. The Portfolio Constraints Model Heuristic.



A.1.3.1. Parameters of Portfolio Constraints Model

For the numeric examples, we set the period to be one year. Households discount the future at a rate of 4 percent ($\beta = .9615$). We assume the utility function is CRRA,

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

and that the household has a standard risk aversion parameter of $\sigma = 2$.

We set the initial endowment $y_0 = 1$. The house price is given by $P_0 = 4.3 \cdot y_0$ to match the annual income to the house price ratio.[24] We choose m such that $\frac{m}{y_0} = .21$ to match the median back-end debt-to-income ratio in the 2009 Panel Study of Income Dynamics (PSID). We evaluate the model at various values of remaining principal, x_0, and we set next year's principal balance to reflect the mortgage payment $x_1 = x_0 - m$.[25] We assume the savings rate is 4 percent, and we set the borrowing rate to 12 percent to match the real historic credit card borrowing rate (Herkenhoff (2013)).

From the 2007 Survey of Consumer Finances (SCF) we set the credit limit-to-annual income ratio to 40 percent, which implies $\phi = .4 \cdot y_0$. Wealth is set to match the 2007 SCF median liquid wealth-to-annual income ratio of $w = 0.04$.[26]

We assume that the distribution of households across beliefs over the state of the world at date 1 is uniform, $p_L \sim U[0, 1]$. House prices in each state of the world are given by $P_1(H) = 1.2$ and $P_1(L) = .8$, and labor income is given by $y_1(L) = .54$ and $y_1(H) = 1$ (In the low state, households are 'unemployed,' and the income replacement rate is 54 percent

[24] The median house price in 2009 was $216,000 (`http://www.census.gov/const/uspriceann.pdf`). The median household income was $50,221 (Census).

[25] For simplicity, we assume that the mortgage interest rate is zero.

[26] See Herkenhoff (2013) for credit limit and wealth data in the SCF.

as in the OECD Benefits Database for the United States).

A.1.3.2. Portfolio Constraints Model, Simulation Exercise

To illustrate the interaction between income loss and negative equity in this simple model, we vary the initial conditions (date 0 income, equity, etc.) of the economy and compare 'Date 0 Default Rates' (defined below). In all of the experiments below, we hold the distribution of house price beliefs $G(p_L)$ constant. Let $\mathbf{x} = (y_0, P_0, w, m)$ denote the initial state vector of the economy. Let $d(p_L, y_0, P_0, w, m) = d(p_L, \mathbf{x})$ denote the date 0 default policy function of an *individual household* with beliefs p_L, initial income y_0, initial house price P_0, initial wealth w, and mortgage payment m. Define the 'Date 0 Default Rate' by integrating the individual date 0 default policy function over future beliefs p_L:

$$\text{`Date 0 Default Rate'} = D(\mathbf{x}) = \int d(p_L, \mathbf{x})\ dG(p_L).$$

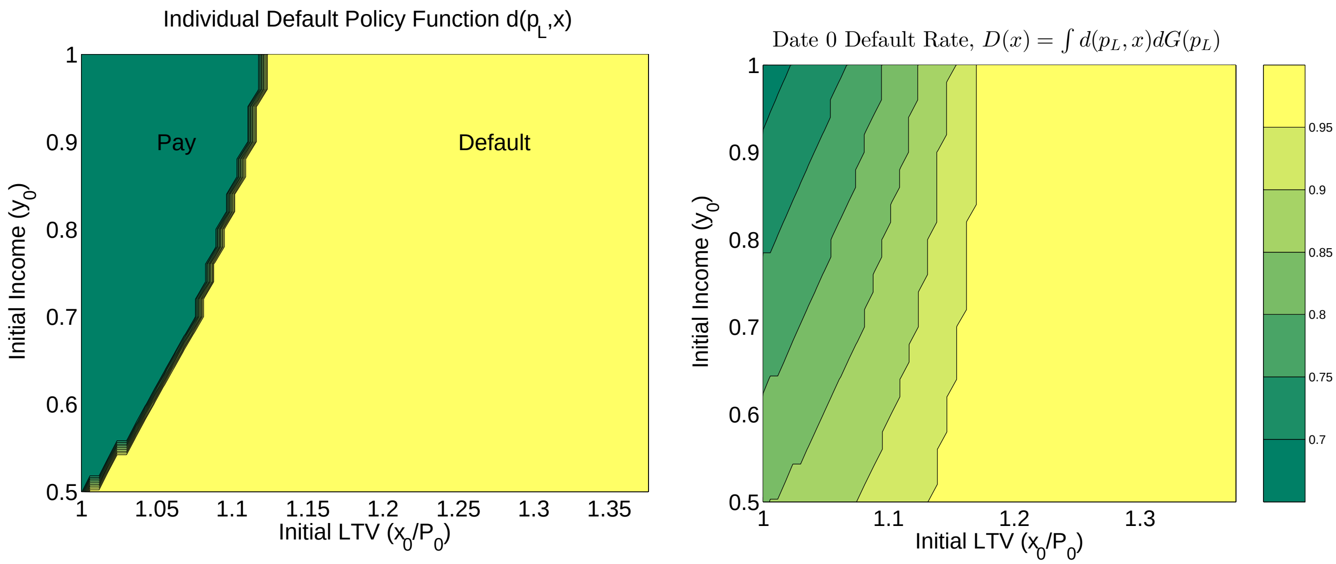
The experiment consists of varying the initial conditions $\mathbf{x}' = (y_0', P_0', w', m')$ of the economy and comparing the date 0 default rates. In explaining the results below, we interpret the economy with initial income $y_0 = 1$ as a representative 'employed' household. We interpret the economy with initial income $y_0' = .54$ as a representative 'unemployed' household.

A.1.3.3. Portfolio Constraints Model, Simulated Default Behavior

Panel (A) of Figure A.4 illustrates an individual household's default policy function. For an individual household, the default policy function is binary. With low initial income, the household defaults regardless of equity. With high initial income, the household defaults only with severe negative equity. In a standard option theoretic model (Schwartz and Torous (1989), Kau and Keenan (1995), etc.), the division between the payment default regions would be a vertical line intersecting the x-axis at a single LTV ratio.

Panel (B) is a contour map that illustrates the 'Date 0 Default Rate.' Lighter color regions indicate *severe* default risk. The default rate is 95 percent with severe negative equity (20 percent or more underwater), but in regions with more moderate levels of negative equity, the default rate is less than 70 percent and hinges critically on initial income. This type of interaction between income and negative equity is pervasive in our empirical results. However, the levels of default are far from those in the data.

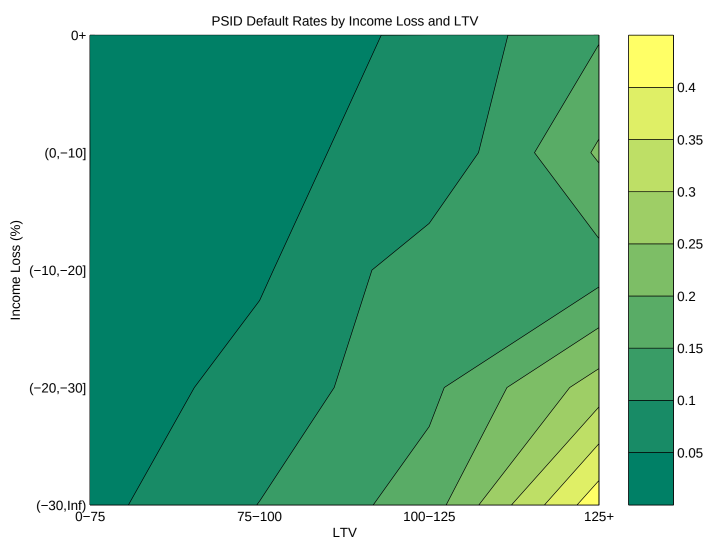
Figure A.4. Default Policy Function and Default Contour Map for 2-Period Model Economy.



A.1.3.4. Data Counterpart to Portfolio Constraints Model: PSID Default Contour Map

Turning to the data, Figure A.5 illustrates default rates, defined to be 60+ days late on the mortgage payment, by income loss (measured between survey dates on gross family income) and LTV ratios (measured as of the survey date). We see a similar gradual increase in default rates in the data as negative equity becomes more severe. However, the level of defaults differs between the model and data. The maximum default rate in the data for those with 25 percent negative equity is 40 percent, whereas in the model, agents with 25 percent negative equity default with 95 percent probability. These low rates of default in the data, even among households that have an empty budget set (from the econometrician's perspective), are puzzling for a broad class of model used to study mortgage default, including the present model, which itself nests the frictionless, double trigger, and portfolio constraints models.

Figure A.5. Empirical Default Rates by Income Loss and Loan to Value Ratio (Source: 2007–2011 PSID)



B.1. SCF Data

We use the 2007–2009 Survey of Consumer Finances (SCF) panel dataset to double check our PSID results. Similar to the PSID, the SCF collected default information in the 2009 wave of interviews. However, the confounding factor in the SCF is the timing and precision of the questions. The main problems include the following: (i) the default question in the SCF refers to default over the last 12 months and is not confined to simply secured debt (let alone mortgages), (ii) there is no separate category for health expenses (the closest is medical loans which are included with "other" loans), (iii) there are no data on consecutive employment spells, and (iv) default status at the survey date is unknown and, since they record negative equity, wealth, and employment as of the survey date, there is severe time aggregation bias.

There are some benefits, however, since the SCF includes measures of credit limits as of the survey date (see Elul et al. (2010)), and credit denial between the 2007 and 2009 survey dates. Unfortunately, in any study with prior default over the last 12 months as the dependent variable and credit utilization as the independent variable, there is severe endogeneity.

In terms of observations, the overall sample size of the SCF is also considerably smaller, but the SCF specifically samples high-net-worth individuals, which is useful in the discussion of strategic default. For the purpose of comparability, we restrict the sample to working age heads of households (24 years to 65 years) who are labor force participants, have a mortgage in 2009, and have combined loan to value ratios below 250 percent. We are left with N=1,299 mortgagors.

B.1.1. Definition of Shocks and Summary Statistics in the SCF

Default is defined as being 60 + days late on any type of debt over the prior 12 months. We define combined loan to value (LTV) ratios in the identical manner as in the main PSID analysis, combining the first and second value of the mortgage and then taking this as a ratio to the self-reported home value. The indicator "Unemployed (d)" ((d) stands for dummy) takes a value 1 when the head is unemployed as of the survey date or spent at least one month unemployed over the prior year. A parallel definition is used for the spouse. "Low Liquid Assets (d)" takes the value 1 when the combined value of savings/checking, CDs, and savings bonds falls below one month's mortgage payment. "Divorce (d" takes a value 1 if the household recently experienced divorce. The "High Unsecured Debt (d)" dummy takes a value of 1 when the value of unsecured debts exceeds five months' mortgage payments.

Table B.1 summarizes the SCF variables of interest. While there are only 1,299 observations, we have 103 observations of default, where default is defined to be 60+ days late over the prior 12 months *on any debt*, which is roughly the same number of observations of default as in the PSID in any given year (however, the PSID measure of default is different and is measured as of the survey date). Similar to the PSID, in the SCF 83 percent of the heads are male and the average age is 44, which is comparable to the PSID sample in Table 2. Mean income is identical (rounded to the neared 000) in both the SCF sample and the PSID sample.

In terms of financial health, 11.3 percent of the entire sample have a combined loan to value ratio over 100 percent. Almost 18 percent of SCF mortgagors have less in liquid assets (savings, checking, CDs, and savings bonds) than one month's mortgage payment. Moreover, 1.2 percent of the sample have a ratio of unsecured debt balances (credit card, retail card, and other unsecured balances) to monthly mortgage payment of over five. The median SCF household also has an unsecured revolving credit line of $20,000 (this is the combined limit across credit cards), which is unobserved in the PSID.

Turning to the defaulter versus average mortgagor comparison, the SCF exhibits the same unemployment pattern as the PSID: only 8 percent of the entire mortgage sample had a head who was unemployed (defined above as being unemployed as of the survey date or unemployed at least one month during the prior year), whereas 29.1 percent of defaulters had a head who was unemployed. Of importance is the fact that defaulters in the SCF have *significantly* lower incomes than the average SCF mortgagor, roughly $50,000 lower.

There is also an interesting correlation between credit denial and default; roughly 38 percent of defaulters were denied credit between 2007 and 2009 versus 16 percent for the entire mortgagor sample. The typical story is that defaulters have low credit scores, and therefore are denied credit more often. A more interesting question is whether or not credit denial leads to default.

B.1.2. SCF Results

Table B.2 reports the OLS regression of the SCF default indicator on equity, unemployment, and other shocks. This table corresponds to Table 4 for the PSID. Column (4) is the most basic specification, which includes LTV and unemployment shocks, but no other controls. As we add controls in column (3) and other shock variables in column (2), the importance of both the LTV ratio and unemployment diminish, but the overall (as well as relative) magnitudes of the coefficients on LTV and the unemployment dummy are nearly identical to those in Table 4 for the PSID. In column (2), unemployment is equivalent to a 49 percent (=.076/.153) reduction in home equity. Likewise, spousal unemployment is equivalent to a 48 percent (=.074/.153) decline in home equity. Among other non-equity shocks, divorce and high amounts of unsecured debt are insignificant, but the presence of low liquid assets is by far the strongest determinant of default. Column (1) allows for unemployment and equity to

Table B.1: SCF, Summary Statistics

	Demographics							
	All Households				**Delinquent Households**			
	Mean	p10	p50	p90	Mean	p10	p50	p90
Age	44.359	31	45	57	42.322	30	43	54
Male (d)	0.833	0	1	1	0.755	0	1	1
Married (d)	0.703	0	1	1	0.649	0	1	1
HS	0.272	0	0	1	0.456	0	0	1
Some College	0.236	0	0	1	0.217	0	0	1
College +	0.443	0	0	1	0.186	0	0	1
	Income and Wealth							
	All Households				**Delinquent Households**			
	Mean	p10	p50	p90	Mean	p10	p50	p90
Total Income	110,000	34,000	82,000	190,000	60,000	26,000	50,000	110,000
Liquid Wealth	29,000	400	6,200	59,000	2,209	20	600	5,600
Illiquid Wealth	26,000	0	0	45,000	4,990	0	0	10,000
Credit Limit	40,000	0	20,000	80,000	11,000	0	2,000	35,000
Denied Credit (d)	0.162	0	0	1	0.375	0	0	1
	Mortgage Characteristics							
	All Households				**Delinquent Households**			
	Mean	p10	p50	p90	Mean	p10	p50	p90
Mortgage Payment	1,306	550	1,100	2,300	1,268	440	1,100	2,400
Negative Equity (d)	0.113	0	0	1	0.303	0	0	1
Default (d)	0.095	0	0	0	1	1	1	1
LTV	0.64	0.23	0.61	1.03	0.92	0.47	0.86	1.55
Second Mortgage (d)	0.1	0	0	1	0.097	0	0	0
Refinanced (d)	0.162	0	0	1	0.153	0	0	1
Variable Rate Mortgage (d)	0.14	0	0	1	0.244	0	0	1
Interest Rate *100	595	475	585	725	660	525	625	900
Term > 15 (d)	0.782	0	1	1	0.864	0	1	1
	Non-Equity Shocks							
	All Households				**Delinquent Households**			
	Mean	p10	p50	p90	Mean	p10	p50	p90
Head Unemployed (d)	0.13	0	0	1	0.291	0	0	1
Spouse Unemployed (d)	0.076	0	0	0	0.14	0	0	1
Liquid Wealth Shock	0.188	0	0	1	0.64	0	1	1
Recent Divorce (d)	0.029	0	0	0	0.053	0	0	0
Unsecured Shock (d)	0.012	0	0	0	0	0	0	0
	Obs.	1299			Obs.	103		

Notes: 2007-2009 SCF Panel. Sample includes working age heads of households (24yrs to 65yrs) who are labor force participants, have a mortgage in 2009, and have CLTVs less than 250 percent. Default is defined as being 60 + days late on any type of debt over the prior 12 months. Credit limits refer to unsecured revolving credit. Denial is measured as any type of loan rejection over the prior two years (for the 2009 cohort), regardless of whether the household was able to later obtain the loan. See text for definition of shocks. (d) indicates a dummy variable.

interact. The coefficient on the interaction term shows that being unemployed roughly triples the propensity to default for any given equity shocks. In Table B.3 we include additional variables in the regression, such as a household's credit limit (aggregate unsecured revolving credit limits, for example credit cards) and previous loan denial status (measured as a denial of any form between 2007 and 2009), which are unobservables in the PSID. Table B.3 shows that the interaction between unemployment and equity is unchanged, with unemployment tripling the effect of any given equity reduction.

Overall, Tables B.2 and B.3, both based on the SCF, confirm the PSID patterns illustrated in Table 4 and mitigate concerns regarding the effects of unobserved credit limits/credit denials in the PSID.

Table B.2: SCF, Baseline Regression. Dependent Variable is Default Indicator in Prior 12 Months to Survey Date on Any Type of Debt (Source: SCF)

	(1)	(2)	(3)	(4)
LTV	0.126***	0.153***	0.193***	0.214***
	(4.06)	(5.01)	(5.82)	(7.49)
Unemployed (d)	-0.067	0.076**	0.107***	0.120***
	(-1.32)	(2.42)	(3.27)	(3.67)
LTV * Unemployed (d)	0.228***			
	(2.64)			
Spouse Unemployed (d)	0.077**	0.074*	0.088**	0.080**
	(2.00)	(1.91)	(2.23)	(2.06)
Low Liquid Assets (d)	0.212***	0.213***		
	(6.26)	(6.27)		
Divorce (d)	0.050	0.052		
	(0.94)	(0.97)		
High Unsecured Debt (d)	-0.036	-0.037		
	(-0.59)	(-0.63)		
Demographic Controls	Y	Y	Y	N
Mortgage Controls	Y	Y	Y	N
State Controls	Y	Y	Y	N
Observations	1,299	1,299	1,299	1,299
R-squared	0.215	0.208	0.140	0.102

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: 2007–2009 SCF Panel. Sample includes working age heads of households (24yrs to 65yrs) who are labor force participants, have a mortgage in 2009, and have CLTVs less than 250 percent. Default is defined as being 60 + days late on any type of debt over the prior 12 months. See text for definition of shocks. Controls include demographic controls for age, rage, sex, marital status, and education; and mortgage controls for the presence of a second mortgage, whether there are 15 or more years remaining on the term of the loan, a prior refinancing, and whether the mortgage is an ARM. (d) indicates a dummy variable.

Table B.3: SCF, Controls for Credit Access. Dependent Variable is Default Indicator in Prior 12 Months to Survey Date on Any Type of Debt (Source: SCF)

	(1)	(2)
LTV	0.112***	0.126***
	(3.61)	(4.02)
Credit Limit	-0.000	-0.000
	(-0.58)	(-0.58)
Denied Credit (d)	0.071**	
	(2.42)	
Unemployed (d)	-0.065	-0.068
	(-1.27)	(-1.33)
LTV * Unemployed (d)	0.226***	0.228***
	(2.59)	(2.64)
Spouse Unemployed (d)	0.074*	0.077**
	(1.93)	(1.99)
Low Liquid Assets (d)	0.205***	0.212***
	(5.95)	(6.25)
Divorce (d)	0.046	0.050
	(0.84)	(0.94)
High Unsecured Debt (d)	-0.043	-0.036
	(-0.68)	(-0.59)
Demographic Controls	Y	Y
Mortgage Controls	Y	Y
State Controls	Y	Y
Observations	1,299	1,299
R-squared	0.223	0.215

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: 2007–2009 SCF Panel. Sample includes working age heads of households (24yrs to 65yrs) who are labor force participants, have a mortgage in 2009, and have CLTVs less than 250 percent. Default is defined as being 60 + days late on any type of debt over the prior 12 months. See text for definition of shocks. Controls include demographic controls for age, rage, sex, marital status, and education; and mortgage controls for the presence of a second mortgage, whether there are 15 or more years remaining on the term of the loan, a prior refinancing, and whether the mortgage is an ARM. (d) indicates a dummy variable.

B.1.3. The Wealth of Defaulters in the SCF

Table B.4 illustrates the ratio of monthly mortgage payments to 'resources-on-hand' (including income, credit limits, and liquid wealth) for households in the SCF. Unlike the PSID, the SCF includes measures of available credit, and as outlined in the model in Section A.1, a necessary condition for default is insufficient credit, income, and wealth (liquid wealth) combined to make one month's mortgage payment. Table B.4 is our (imperfect) attempt to measure how close people are to this sufficient condition for default.[27] The first row of Table B.4 shows that if we add up monthly income (annual family gross income divided by 12), plus unsecured revolving credit limits, plus liquid wealth, the median defaulting SCF mortgagor can make 10 mortgage payments. If we adjust for the fraction of the credit limit being used, and we set monthly income to zero when the head is unemployed (as of the survey date), then the median defaulting household can make 6.25 (=1/.16) mortgage payments with resources on hand. The 75th percentile can make only 1.29 (=1/.77) mortgage payments, while the 90th percentile can make only 1.25 (=1/.80) mortgage payments. If we drop credit resources from the definition of resources on hand, the situation worsens significantly, with the median household able to make only five mortgage payments (=1/.2), the 75th percentile able to make approximately one mortgage payment (=1/.9), and the 90th percentile only able to make one-half of one mortgage payment (=1/1.87). Among nondefaulters, in every specification, the median household could afford at least 10 months' mortgage payments from resources on hand. Table B.5 shows that defaulters had unused credit limits worth 3.6 $\times$ the value of their mortgage payment, on average.

[27] The fundamental problem with the SCF is two-fold: (1) no monthly measure of income (as of the survey date), and (2) time aggregation bias.

Table B.4: Ratio of Mortgage Payments to Resources, (Source: SCF)

	All Defaulters, Weighted							
	Mean	p10	p25	p50	p75	p90	sd	N
Mortgage Payment to Total Resources (Total Resources= Average Monthly Income+Credit Limit+Liquid Wealth)	0.17	0.02	0.06	0.11	0.18	0.31	0.34	103
Mortgage Payment to Unused Total Resources (Unused Total Resources= Average Monthly Income+Unused Credit Limit+Liquid Wealth)	0.21	0.05	0.09	0.16	0.22	0.46	0.36	103
Mortgage Payment to Employment Adjusted Unused Total Resources (Employment Adjusted Unused Total Resources= Average Monthly Income IF EMPLOYED+Unused Credit Limit+Liquid Wealth)	0.34	0.05	0.09	0.16	0.22	0.77	0.80	99
Mortgage Payment to Non-Credit Resources (Non-Credit Resources= Average Monthly Income+Liquid Wealth)	0.30	0.08	0.12	0.20	0.29	0.48	0.64	103
Mortgage Payment to Employment Adjusted Non-Credit Resources (Employment Adjusted Non-Credit Resources= Average Monthly Income IF EMPLOYED+Liquid Wealth)	0.61	0.08	0.12	0.20	0.31	0.90	1.87	99
	All Mortgagors, Weighted							
	Mean	p10	p25	p50	p75	p90	sd	N
Mortgage Payment to Total Resources (Total Resources= Average Monthly Income+Credit Limit+Liquid Wealth)	0.06	0.01	0.01	0.03	0.06	0.15	0.17	1299
Mortgage Payment to Unused Total Resources (Unused Total Resources= Average Monthly Income+Unused Credit Limit+Liquid Wealth)	0.07	0.01	0.02	0.03	0.08	0.18	0.20	1299
Mortgage Payment to Employment Adjusted Unused Total Resources (Employment Adjusted Unused Total Resources= Average Monthly Income IF EMPLOYED+Unused Credit Limit+Liquid Wealth)	0.09	0.01	0.02	0.03	0.08	0.19	0.32	1294
Mortgage Payment to Non-Credit Resources (Non-Credit Resources= Average Monthly Income+Liquid Wealth)	0.12	0.02	0.04	0.08	0.14	0.24	0.25	1299
Mortgage Payment to Employment Adjusted Non-Credit Resources (Employment Adjusted Non-Credit Resources= Average Monthly Income IF EMPLOYED+Liquid Wealth)	0.17	0.02	0.04	0.08	0.15	0.25	0.70	1292

Notes: 2007–2009 SCF Panel. Sample includes working age heads of households (24yrs to 65yrs) who are labor force participants, have a mortgage in 2009, and have CLTVs less than 250 percent who were 60+ days late over prior 12 months on any type of debt. Average monthly income computed as gross family income divided by 12. Credit limits defined to be unsecured revolving credit limits. Liquid assets include saving/checking balances, CDs, and savings bonds.

Table B.5: SCF, Unused Credit Limits to Mortgage Payments

	Mean	p25	p50	p75	N
Unused Credit Limit to Mortgage Payment, Defaulters	3.643	0	0.417	2.548	103
Unused Credit Limit to Mortgage Payment, Defaulters Wtd.	3.076	0	0	2.5	103
Unused Credit Limit to Mortgage Payment, All Mortgagors	35.689	4.375	14.706	32.611	1298
Unused Credit Limit to Mortgage Payment, All Mortgagors Wtd.	26.415	2.222	12.501	29.299	1298

Notes: 2007–2009 SCF Panel. Sample includes working age heads of households (24yrs to 65yrs) who are labor force participants, have a mortgage in 2009, and have CLTVs less than 250 percent who were 60+ days late over prior 12 months on any type of debt. Average monthly income computed as gross family income divided by 12. Unused credit limits defined to be unsecured revolving credit limits less balances.

C.1. Alternate Definition of Unemployment

Table C.1 illustrates our main results when we restrict the definition of the unemployment shock to be those who are unemployed as of the survey date. We find nearly identical results as in our main table in the text. Column (1) of Table C.1 is a linear regression of a default indicator of job loss and loan to value ratios, omitting controls. Column (2) adds in demographic, mortgage, and state controls. Column (3) adds in individual financial shocks other than job loss. This is the main specification, and in this case job loss is equivalent to an 80 percent reduction in equity (=.072/.088). The interaction between equity and unemployment in column (4) is large but insignificant, likely due to the power of the hypothesis test with so few unemployment observations. Columns (5) and (6) show that state-level unemployment controls are insignificant, very small in magnitude, and often have the wrong sign relative to the individual unemployment indicators.

Table C.1: Alternate Definition of Unemployment: Unemployed As of Survey Date

	(1)	(2)	(3)	(4)	(5)	(6)
LTV	0.096***	0.094***	0.088***	0.081***	0.096***	0.031
	(8.41)	(6.71)	(6.30)	(5.68)	(6.88)	(0.60)
Unemployed (d)	0.092***	0.076***	0.072***	0.011		
	(5.06)	(4.20)	(4.08)	(0.32)		
LTV * Unemployed (d)				0.085		
				(1.58)		
Spouse Unemployed (d)	0.020	0.023	0.017	0.017		
	(1.02)	(1.19)	(0.89)	(0.88)		
Low Liquid Assets (d)			0.054***	0.054***		
			(6.55)	(6.51)		
High Hospital Bills (d)			0.045	0.044		
			(1.42)	(1.38)		
High Medical Bills (d)			0.005	0.005		
			(0.88)	(0.88)		
Divorce (d)			0.033	0.033		
			(1.17)	(1.18)		
High Unsecured Debt (d)			0.002	0.003		
			(0.15)	(0.22)		
State UR					-0.000	-0.005
					(-0.05)	(-1.34)
State UR * LTV						0.007
						(1.22)
Demographic Controls	N	Y	Y	Y	Y	Y
Mortgage Controls	N	Y	Y	Y	Y	Y
State Controls	N	Y	Y	Y	Y	Y
Observations	5,281	5,281	5,281	5,281	5,281	5,281
R-squared	0.045	0.085	0.099	0.100	0.075	0.075

Notes: (d) indicates a dummy variable.

D.1. Nonlinear Interactions Between Unemployment and Equity

D.1.1. Estimation of Spline Kinks

Our two-period, portfolio-constraints model predicts a nonlinear relationship between job loss and negative equity in the decision to default. To better capture this nonlinear relationship, we model the relationship between LTV ratios and default rates using a linear spline, allowing the spline to differ between employed and unemployed households when the LTV ratio crosses a certain threshold (a knot). Since the predictions of theory and empirical evidence tell us that default is infrequent for households with positive equity, we restrict the interaction between unemployment and equity to be zero for low loan to value ratios.[28] Thus, we allow an interaction between unemployment and the LTV ratio only after the first cutoff (the first cutoff will be an LTV ratio of 88—this is intuitive, since transaction costs and taxes make an LTV ratio of 88 close to the cusp of effective negative equity). Let $i \in \{1, \ldots, N\}$ index the observations; let d_i denote the realized default outcome; let variables with a hat be estimates; and let LTV_i denote the combined LTV ratio of household i. We choose the knots of the spline (the location of the kinks), denoted by c_i, by estimating the following nonlinear least squares problem:

$$\min_{\{b_k\}_{k=1}^{k=6}, c_1, c_2} \sum_{i=1}^{N} \|d_i - \hat{d}_i\|^2$$

such that

$$\begin{aligned}
\hat{d}_i =& b_0 + b_1 \cdot LTV_i \cdot \mathbb{I}_{LTV_i < c_1} \\
&+ \{b_1 c_1 + b_2(LTV_i - c_1) + b_4(LTV_i - c_1)\mathbb{I}_{Unempl_i}\}\mathbb{I}_{c_1 < LTV_i < c_2} \\
&+ \{b_1 c_1 + b_2(c_2 - c_1) + b_4(c_2 - c_1) \cdot \mathbb{I}_{Unempl_i} + b_3(LTV_i - c_2) + b_5(LTV_i - c_2)\mathbb{I}_{Unempl_i}\}\mathbb{I}_{LTV_i > c_2} \\
&+ b_6 \mathbb{I}_{Unempl_i}\ , \quad \forall i \in \{1, \ldots, N\}.
\end{aligned}$$

Table D.1 presents the results of the nonlinear least squares estimation for the knots of the spline. The first knot is located at an LTV of 88 percent, and the second knot is at an LTV of 125 percent. In the absence of interaction terms between the unemployment shock and the LTV ratio, a similar set of knots emerges (an LTV of 91 percent for the first knot and an LTV of 121 percent for the second knot). The interpretation of this result is

[28] We experimented with the specification and found that the interaction is, in fact, close to zero for low LTV ratios.

as follows: there are interactions between unemployment and equity for moderate levels of negative equity (LTVs between 88 and 125), but with either severe negative equity or a great deal of positive equity, the unemployment shock does not interact with equity.

Table D.1: Estimation of Spline Kinks, Nonlinear Least Squares.

		NLS
LTV, Up to 1st Kink	b_1	0.025
		(1.94)
LTV Cutoff 1st Kink	c_1	0.884***
		(24.52)
LTV, Middle Segment	b_2	0.237***
		(5.23)
LTV*Unemployed, Middle Segment	b_4	0.394*
		(2.56)
LTV Cutoff 2	c_2	1.250***
		(11.65)
LTV, Past Last Kink	b_3	0.176***
		(5.01)
LTV * Unemployed, Past Last Kink	b_5	-0.190
		(-1.76)
Unemployed	b_6	0.053***
		(5.24)
# Households		5,281
R^2		0.056

Notes: t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. PSID sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011.

D.1.2. Interaction Results

In Table D.2, we present estimation results from the linear spline specification (for the LPM). The spline's cutoffs are taken from Section D.1.1, but the initial intercept and slopes are estimated in each regression separately. To understand what the spline coefficients mean, consider column (1), which is the simplest specification (no controls or interaction terms). The slope of the spline function for moderate levels of negative equity (LTV ratios between 88 and 125) is large and significant. In this region, a price decline of 20 percent would increase the default propensity by 5.6 percentage points (0.2*0.28=.056), on average, other things being equal. Job loss (of the head) would increase the default propensity by 6.6 percentage points, on average. Column (2) introduces controls, and column (3) allows for other shocks. Among the other shocks, low liquid assets is strongly correlated with default, consistent with results from the simpler specification discussed above.

Column (4) of Table D.2 allows for interactions between the unemployment shock and LTV ratios greater than 88 percent. We find that the interaction between moderate levels of negative equity is large and significant, but for severe negative equity (LTV $>$ 125 percent), default is essentially independent of job loss. One interpretation of this finding is that households that are deeply underwater are no longer as sensitive to job loss (or other financial shocks) and simply exercise the default option based on their current equity position and low expectations of future prices. This is consistent with Bhutta, Dokko, and Shan (2011), among others. The interaction term can be interpreted as follows: Imagine a household with an LTV ratio of 100 percent. Suppose the house value falls by 20 percent and the LTV ratio climbs to 120 percent. For an employed household, this increases the default propensity by 3.4 percentage points (0.2*0.17=0.034), whereas for an unemployed household this increases the default propensity by 11.7 percentage points (0.2*[0.17+0.413] = 0.117).

Table D.2: Linear Probability Model with Linear Spline in Equity

Dependent Variable: 60+ Days Delinquent Indicator				
	(1)	(2)	(3)	(4)
LTV<88% Spline	0.023**	0.019	0.013	0.014
	(2.41)	(1.54)	(1.04)	(1.10)
88%< LTV <125% Spline	0.281***	0.231***	0.208***	0.166***
	(4.67)	(3.89)	(3.53)	(2.80)
LTV >125% Spline	0.148**	0.153**	0.164**	0.188**
	(2.05)	(2.16)	(2.33)	(2.54)
Unemployed (d)	0.066***	0.053***	0.049***	0.034**
	(4.63)	(3.74)	(3.55)	(2.49)
Spouse Unemployed (d)	0.034**	0.040**	0.034**	0.034**
	(2.08)	(2.46)	(2.11)	(2.14)
Low Liquid Assets (d)			0.054***	0.054***
			(6.63)	(6.61)
High Hospital Bills (d)			0.039	0.037
			(1.22)	(1.15)
High Medical Bills (d)			0.003	0.003
			(0.54)	(0.54)
Recently Divorced (d)			0.037	0.036
			(1.33)	(1.32)
High Unsecured Debt (d)			0.001	0.001
			(0.07)	(0.07)
88%< LTV <125% Spline * Unemployed (d)				0.413*
				(1.82)
LTV >125% Spline * Unemployed (d)				-0.221
				(-0.95)
Demographic Controls	N	Y	Y	Y
Mortgage Controls	N	Y	Y	Y
State Controls	N	Y	Y	Y
# Households	5,281	5,281	5,281	5,281
R^2	0.055	0.091	0.105	0.108

Notes: Slopes of spline segment reported. t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. (d) indicates a dummy variable

E.1. Alternative Definitions of "Can't Pay" and "Won't Pay"

E.1.1. "Can't Pay" and "Won't Pay" Households with Negative Home Equity

Table E.1 repeats the statistics in Table 8, including only those with negative equity (that is, LTV>1). Panel (A) of Table E.1 shows that the sample of households with negative equity also have significantly lower income. Only about 5 percent of the "can pay" households with negative equity default, whereas 33 percent of "can't pay" households with negative equity default. However, the sample sizes are extremely small (but this confirms the point made in the paper—not many households default, and of those that do default, few appear to be "can pay" households).

E.1.2. "Can't Pay" and "Won't Pay" Households, Alternate Definitions with Both Head and Spouse Out of Work

Table E.2 repeats the statistics in Table 8 with alternate definitions of "can pay" and "can't pay." The alternate definition of "can pay" includes all households who have had no unemployment spells and have one of either (i) at least six months' worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt or (ii) a DTI< 31 percent. "Can't pay" households have both (i) an unemployed head and a non-employed spouse and (ii) less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Panel (A) of Table E.2 shows that even under this definition of "can't pay," only 27 percent default, whereas 73 percent continue to pay.

E.1.3. Collectively Exhaustive Definitions of "Can't Pay"

Table E.3 includes a definition of "can't pay"/"can pay" that splits all households into two groups, mutually exclusive and collectively exhaustive. We define "can't pay" households as before. However, we compare them with the new group of "can pay" households, which we define to be " everyone else." We label the "can't pay" households in the dataset, and then compare them to "everyone else." As Table E.3 illustrates, about one-third of "can't pay" households default, whereas "everyone else" defaults at a very low default rate of 3 percent or lower.

Table E.1: "Can't Pay" and "Won't Pay" Summary Statistics, Conditional on Negative Home Equity, LTV>1

	Can Pay LTV>1		Can't Pay LTV>1		Won't Pay LTV>1		Don't Pay LTV>1	
(A) Demographics								
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
White (d)	0.68	1	0.56	1	0.44	0	0.31	0
Black (d)	0.25	0	0.21	0	0.56	1	0.15	0
Age	41.31	40	42.80	41	41.67	38	41.62	41
Male (d)	0.83	1	0.74	1	0.67	1	0.92	1
Married (d)	0.72	1	0.56	1	0.44	0	0.69	1
Less than High School (d)	0.06	0	0.23	0	0.00	0	0.23	0
High School Education (d)	0.19	0	0.36	0	0.11	0	0.39	0
Some College Education (d)	0.22	0	0.18	0	0.56	1	0.15	0
College Grad+ Education (d)	0.51	1	0.23	0	0.33	0	0.23	0
Number of Children	1.08	1	0.90	0	1.44	1	0.69	0
Income	110,000	97,000	53,000	57,000	92,000	67,000	52,000	62,000
(B) Mortgage Characteristics								
	Can Pay LTV>1		Can't Pay LTV>1		Won't Pay LTV>1		Don't Pay LTV>1	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Home value	210,000	160,000	130,000	99,000	190,000	110,000	190,000	130,000
Principal Remaining	230,000	200,000	140,000	120,000	280,000	200,000	200,000	160,000
Monthly Mortgage Payment	1,575	1,326	1,104	1,086	2,149	1,850	1,499	1,400
Second Mortgage (d)	0.29	0	0.26	0	0.44	0	0.39	0
Refinanced Mortgage (d)	0.36	0	0.44	0	0.22	0	0.39	0
ARM (d)	0.12	0	0.23	0	0.22	0	0.46	0
Mortgage Interest Rate	5.08	5	5.62	6	4.33	6	5.54	5
Mortgage Term Remaining	24.00	26	23.68	25	26.78	26	24.69	25
Recourse (d)	0.32	0	0.33	0	0.00	0	0.39	0
Judicial (d)	0.21	0	0.31	0	0.33	0	0.31	0
Default (60+ Days Late) (d)	0.05	0	0.33	0	1.00	1	1.00	1
Months Delinquent	0.31	0	2.18	0	5.44	4	6.31	4
Loan to Value Ratio	1.27	1.15	1.36	1.25	1.61	1.68	1.32	1.25
(C) Employment								
	Can Pay LTV>1		Can't Pay LTV>1		Won't Pay LTV>1		Don't Pay LTV>1	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Unemployed Head Last Year (d)	0.02	0	1.00	1	0.00	0	1.00	1
Unemployed Spouse Last Year (d)	0.06	0	0.13	0	0.11	0	0.31	0
Unemployed Head or Spouse Last Year (d)	0.08	0	1.00	1	0.11	0	1.00	1
Head Unemployed as of Survey Date (d)	0.00	0	1.00	1	0.00	0	1.00	1
Spouse Unemployed as of Survey Date (d)	0.07	0	0.16	0	0.00	0	0.30	0
Unemployment Duration	0.09	0	2.08	0	0.00	0	2.31	0
Unemployment Duration, Spouse	0.14	0	0.64	0	0.11	0	1.00	0
(D) Wealth								
	Can Pay LTV>1		Can't Pay LTV>1		Won't Pay LTV>1		Don't Pay LTV>1	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Value of Stocks	37,000	0	113	0	33,000	0	308	0
Value of Liquid Assets	19,000	10,000	3,523	400	8,176	100	454	0
Unsecured Debt	10,000	1,200	22,000	7,500	20,000	20,000	17,000	5,000
Value of Vehicles	17,000	15,000	7,580	6,000	12,000	13,000	7,608	8,000
Value of Bonds	47,000	0	590	0	160,000	0	769	0
Value of Business	4,264	0	189	0	3,750	0	167	0
Value of IRA	19,000	0	2,842	0	0	0	0	0
Value of Other Housing	21,000	0	1,795	0	13,000	0	5,385	0
Value of Liquid Assets	19,000	10,000	3,523	400	8,176	100	454	0
N	174		39		9		13	

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Can Pay: Head employed with negative equity and at least 6 mo. worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Can't pay: Head is unemployed with negative equity and has less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Won't Pay: "Can pay" borrowers who default. Don't Pay: "Can't pay" borrowers who default. (d) indicates a dummy variable.

Table E.2: "Can't Pay" and "Won't Pay" Summary Statistics, Alternate Definitions Based on Unemployed Head and Spouse

(A) Demographics

	Can Pay Alt Def. Mean	Can Pay Alt Def. p50	Can't Pay Alt Def. Mean	Can't Pay Alt Def. p50	Won't Pay Alt Def. Mean	Won't Pay Alt Def. p50	Don't Pay Alt Def. Mean	Don't Pay Alt Def. p50
White (d)	0.76	1	0.52	1	0.40	0	0.40	0
Black (d)	0.19	0	0.33	0	0.48	0	0.44	0
Age	43.21	43	45.27	46	41.08	40.5	44.68	43
Male (d)	0.93	1	0.50	0.5	0.75	1	0.52	1
Married (d)	0.87	1	0.40	0	0.71	1	0.44	0
Less than High School (d)	0.06	0	0.20	0	0.10	0	0.12	0
High School Education (d)	0.23	0	0.29	0	0.23	0	0.36	0
Some College Education (d)	0.26	0	0.25	0	0.42	0	0.16	0
College Grad+ Education (d)	0.45	0	0.26	0	0.23	0	0.36	0
Education Missing (d)	0.01	0	0.01	0	0.02	0	0.00	0
Number of Children	1.03	1	1.12	1	1.31	1	1.16	1
Income	120,000	99,000	45,000	38,000	90,000	79,000	37,000	33,000

(B) Mortgage Characteristics

	Can Pay Alt Def. Mean	Can Pay Alt Def. p50	Can't Pay Alt Def. Mean	Can't Pay Alt Def. p50	Won't Pay Alt Def. Mean	Won't Pay Alt Def. p50	Don't Pay Alt Def. Mean	Don't Pay Alt Def. p50
Home value	270,000	200,000	150,000	110,000	190,000	150,000	200,000	120,000
Principal Remaining	160,000	130,000	110,000	83,000	180,000	160,000	150,000	95,000
Monthly Mortgage Payment	1,358	1,200	928	745	1,457	1,350	1,170	932
Second Mortgage (d)	0.19	0	0.18	0	0.21	0	0.20	0
Refinanced Mortgage (d)	0.47	0	0.36	0	0.42	0	0.24	0
ARM (d)	0.08	0	0.11	0	0.17	0	0.16	0
Mortgage Interest Rate	5.08	5	5.73	6	5.67	6	4.60	5
Mortgage Term Remaining	21.04	24	20.46	23	24.52	26	21.92	24
Recourse (d)	0.25	0	0.28	0	0.33	0	0.24	0
Judicial (d)	0.40	0	0.37	0	0.31	0	0.52	1
Default (60+ Days Late) (d)	0.02	0	0.27	0	1.00	1	1.00	1
Months Delinquent	0.10	0	1.47	0	4.96	3	5.28	4
Loan to Value Ratio	0.71	0.72	0.85	0.82	1.02	0.93	0.82	0.76

(C) Employment

	Can Pay Alt Def. Mean	Can Pay Alt Def. p50	Can't Pay Alt Def. Mean	Can't Pay Alt Def. p50	Won't Pay Alt Def. Mean	Won't Pay Alt Def. p50	Don't Pay Alt Def. Mean	Don't Pay Alt Def. p50
Unemployed Head Last Year (d)	0	0	1	1	0	0	1	1
Unemployed Spouse Last Year (d)	0	0	0.22	0	0	0	0.28	0
Unemployed Head or Spouse Last Year (d)	0	0	1	1	0	0	1	1
Head Unemployed as of Survey Date (d)	0	0	1	1	0	0	1	1
Spouse Unemployed as of Survey Date (d)	0	0	0.45	0	0	0	0.46	0
Unemployment Duration	0	0	2.79	0	0	0	5.60	6
Unemployment Duration, Spouse	0	0	0.49	0	0	0	1.16	0

(D) Wealth

	Can Pay Alt Def. Mean	Can Pay Alt Def. p50	Can't Pay Alt Def. Mean	Can't Pay Alt Def. p50	Won't Pay Alt Def. Mean	Won't Pay Alt Def. p50	Don't Pay Alt Def. Mean	Don't Pay Alt Def. p50
Value of Stocks	24,000	0	6	0	8	0	0	0
Value of Liquid Assets	21,000	6,000	1,647	350	3,202	800	590	0
Unsecured Debt	15,000	4,500	35,000	8,500	20,000	10,000	39,000	15,000
Value of Vehicles	20,000	15,000	10,000	5,000	14,000	7,000	7,444	8,000
Value of Bonds	16,000	0	160	0	34,000	0	0	0
Value of Business	44,000	0	22	0	2,717	0	0	0
Value of IRA	37,000	0	10,000	0	1,756	0	0	0
Value of Other Housing	33,000	0	2,154	0	(208)	0	2,800	0
N		2906		94		48		25

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Can Pay: No unemployment spells for either the head or spouse and either (i) at least six months worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt or (ii) a DTI$<$ 31 percent. Can't pay: Head is unemployed and spouse is non-employed and has less than one month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Won't Pay: "Can pay" borrowers who default. Don't Pay: "Can't pay" borrowers who default. (d) indicates a dummy variable.

Table E.3: Collectively Exhaustive Definitions of “Can’t Pay”/“Can Pay”

	Can’t Pay	**Everyone Else**
Default Rate, Baseline Definition	19.20%	3.00%
N	193	5088
Default Rate, Baseline Definition w/ Negative Equity (CLTV≥1)	33.30%	10.00%
N	39	669
Default Rate, Baseline Definition w/ CLTV≥.9	28.10%	6.70%
N	64	1326
Default Rate, Alternate Definition	26.60%	3.20%
N	94	5187
Default Rate, Alternate Definition w/ Negative Equity (CLTV≥1)	30.40%	10.70%
N	23	685
Default Rate, Alternate Definition w/ CLTV≥.9	24.20%	7.30%
N	33	1357

Notes: PSID Sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent in 2009 and 2011. Baseline Definition of “Can’t Pay”: Head is unemployed and has less than one month’s worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. “Baseline Definition w/ Negative Equity” imposes additional restriction that Combined Loan to Value (CLTV) is greater than or equal to 1. Alternate Definition of “Can’t Pay”: households have both (i) an unemployed head and a non-employed spouse and (ii) less than one month’s worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. “Alternate Definition w/ Negative Equity” imposes additional restriction that Combined Loan to Value (CLTV) is greater than or equal to 1. Everyone else: all households that are not labeled as “can’t pay” households.

F.1. Loans from Relatives

Table F.1 illustrates a decisive lack of borrowing from family members in the 2011 PSID (see Bentolila and Ichino (2008) for a more comprehensive discussion of family borrowing across the world). Table F.1 tabulates the ratio of loans from relatives to the monthly mortgage payment. This measure is designed to capture the ability of households to borrow from relatives to cover mortgage obligations. Among defaulting "can't pay" households, only about 10 percent are receiving assistance from family members in the form of loans. This measure of family borrowing excludes other types of intra-family assistance that may be important for "can't pay" households.

Table F.1: Loans from Relatives, 2011 PSID

	Mean	sd	p10	p50	p90	N
Ratio of Loans from Relatives to Mortgage Payment, All	0.018	0.229	0	0	0	2543
Ratio of Loans from Relatives to Mortgage Payment, Defaulters	0.017	0.114	0	0	0	94
Ratio of Loans from Relatives to Mortgage Payment, All "Can Pay" Households	0.003	0.054	0	0	0	986
Ratio of Loans from Relatives to Mortgage Payment, "Can Pay" Defaulters	0	0	0	0	0	7
Ratio of Loans from Relatives to Mortgage Payment, All "Can't Pay" Households	0.095	0.608	0	0	0	83
Ratio of Loans from Relatives to Mortgage Payment, "Can't Pay" Defaulters	0.026	0.079	0	0	0.062	14

Notes: 2011 PSID sample includes heads of household who are mortgagors, ages 24–65, and are labor force participants with combined loan to value ratios less than 250 percent.