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Unemployment, Negative Equity, and Strategic Default

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Abstract: Using new household-level data, we quantitatively assess the roles that job loss, negative equity, and wealth (including unsecured debt, liquid assets, and illiquid assets) play in default decisions. In sharp contrast to prior studies that proxy for individual unemployment status using regional unemployment rates, we find that individual unemployment is the strongest predictor of default. We find that individual unemployment increases the probability of default by 5–13 percentage points, ceteris paribus, compared with the sample average default rate of 3.9 percent. We also find that only 13.9 percent of defaulters have both negative equity and enough liquid or illiquid assets to make one month's mortgage payment. This finding suggests that "ruthless" or "strategic" default during the 2007–09 recession was relatively rare and that policies designed to promote employment, such as payroll tax cuts, are most likely to stem defaults in the long run rather than policies that temporarily modify mortgages.

JEL classification: E24, E30, G21, E60, D12, D14, E51, G33, L85, R31

Key words: unemployment, mortgage, default, strategic default, negative equity, liquidity constraint

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1. Introduction

The question of what exactly drives mortgage defaults is of central importance in the aftermath of the 2008 U.S. financial crisis and subsequent Great Recession. In order to begin to design policies to alleviate the still-elevated levels of delinquencies and foreclosures, and prevent a future mortgage foreclosure crisis, we need to understand the exact sources of the problem. There is a large and growing literature that studies the empirical determinants of mortgage default.[1] Within this literature, there is broad agreement that a number of factors may potentially contribute to default, including negative equity, employment/unemployment status of the mortgagor, and the net wealth and liquidity position of the mortgagor. Quantifying the relative importance of these factors is important because they have very different implications for understanding default incentives and actions, and also for the design of economic policy. Specifically, if negative equity in and of itself plays a quantitatively important role, then many defaulters may be engaging in what is called strategic, or ruthless default, in which borrowers stop paying when they have a large negative equity position. In contrast, if unemployment plays a key role, then default by many borrowers may simply reflect an inability to make mortgage payments, rather than exercising an option value on an asset whose price has fallen, as would be the case with strategic default.

Despite many studies, there is no definitive answer as to the quantitative importance of these different factors in default decisions.[2] This reflects the fact that existing studies have not used a dataset that simultaneously provides measures of mortgage status, borrower employment/unemployment status, and the asset and liability position of borrowers. Instead, borrower employment status is typically proxied in studies by using the state, county, or MSA unemployment rate. Gyourko and Tracy [2013] shows that this proxy can lead to quantitatively important attenuation bias that substantially understates the role of unemployment in default. Indeed, as we discuss in more detail below, many of the prior studies that have included aggregate unemployment rates have found only a weak correlation with default. Moreover, measures of wealth are omitted in most studies due to the lack of such information in the typical loan-level datasets used by researchers.

Consequently, relatively little is known about the contribution of job loss and borrower net worth positions on default. And this in turn has important implications for assessing the contribution of negative equity, not only because the impact of these other factors is

[1] Foote et al. [2008], Haughwout et al. [2008], Mayer et al. [2009], Gathergood [2009], Goodman et al. [2010], Elul et al. [2010], Bhutta et al. [2011], and Mocetti and Viviano [2013] among others.

[2] For example, Goodman et al. [2010], Bhutta et al. [2011], and Foote et al. [2008] argue that negative equity is the most important factor explaining the rise in defaults during the crisis, Elul et al. [2010] argues that illiquidity in the form of high credit card utilization rates in combination with negative equity are the main factors triggering default, while Mayer et al. [2009] argues that it is a combination of house price stagnation, loose underwriting, and poor employment prospects.

not measured, or not measured well, but also because little is known about the interaction of negative equity with these other factors. As a result, the impact of negative equity as a "single trigger" for default, as would be the case of strategic default, or whether negative equity is important in conjunction with another factor as a "double trigger", is uncertain.

In this paper we begin to disentangle the causes of default using the Panel Study of Income Dynamics (PSID), which includes relatively precise measures of mortgage delinquency, negative equity, employment status, and wealth. In a simple, transparent, reduced-form analysis, we assess the relative importance of these factors in explaining household-level mortgage defaults. We find in contrast to many prior studies that focused on regional unemployment rates, an individual's unemployment status and liquid asset positions are important (and nearly always the most important) determinants of default. To be more precise, we find that individual unemployment increases the probability of default by 8 to 13 percentage points, ceteris paribus, which is a very large effect considering that the unconditional, average default rate in the PSID is only 3.9%. Consistent with prior work by Bhutta et al. [2011], we also find that severe negative equity of -20% or worse increases the probability of default by 5 to 18 percentage points, ceteris paribus. Finally, we find a strong, negative correlation between a household's level of liquid assets and default behavior. Households who report a ratio of liquid assets to annual gross income of over 5% default 3 to 8 percentage points less than households with a ratio under 5%, in line with the liquidity results of Elul et al. [2010]. We corroborate these results in the Survey of Consumer Finances (SCF), which has a similar level of information at the household-level.

In addition, we present suggestive evidence of the importance of double trigger events in causing mortgage defaults. For example, the simple unconditional default rate of unemployed households with negative equity in the PSID is approximately 30%, whereas employed households with negative equity have an unconditional default rate of just over 10%, which implies that unemployment produces a difference in default rates of approximately 20% among those with negative equity. In contrast, the unconditional default rate for an unemployed household with positive equity in the PSID is 10.6% while an employed household with positive equity has a default rate of only 2.1%, which implies that unemployment produces a difference of roughly 8.5% in default rates among those with positive equity. Thus, the simple interaction effect, or the "double trigger" effect, between unemployment *and* negative equity is to raise the unconditional default rate by approximately 11.5% (20% - 8.5%) over and above either trigger on its own. While the sample size in the PSID is too small to precisely estimate the interaction between employment and equity with controls, the large magnitude of the unconditional measure of the double trigger effect of unemployment and negative equity suggests that future research on the double trigger hypotheses is vital.

Finally, with both detailed data on households' balance sheets and home equity positions, we are able to provide some new suggestive measures of strategic default to the literature. We find that in the PSID, less than 14% of defaulters have both negative equity and enough liquid (broadly defined) or illiquid assets to make 1 month's mortgage payment. In the SCF, which deliberately over-samples high-net-worth individuals and provides more disaggregated measures of wealth, only 6% of all defaulters (where default is measured during the 12 months prior to the survey date and includes default on all types of debt) have both negative equity and enough money in their savings or checking accounts to make 1 month's mortgage payment. Such evidence calls into question the importance of ruthless default during the 2007-2009 recession and may suggest that policies designed to promote employment, such as payroll tax cuts, are most likely to stem defaults in the long run.

Section 2 discusses the related literature. Section 3 describes the data. Section 4 describes both the single trigger and double trigger results. Section 5 discusses measures of strategic default using both PSID and SCF data, and finally, Section 6 concludes.

2. Related Literature

The early theoretical literature modeled mortgage default as an option using the contingent claims framework pioneered by Black and Scholes [1973].[3] In that framework the sole determinants of mortgage default are interest rates and home values. There is no role for unemployment or other cash-flow or wealth shocks in the borrower's default decision. However, many early empirical studies found that other variables such as income, unemployment rates, and divorce rates seemed to predict mortgage default rates.[4]

Riddiough [1991] was one of the first papers in the theoretical mortgage default literature to model so-called "trigger events" such as divorce, job loss, health shock, or other accident.[5] Kau et al. [1993] incorporated transactions costs and what they referred to as "suboptimal default," which is just another name for trigger events, and concluded that these events must have a large and important role in option-based models in order to match the data. After this finding, numerous studies began incorporating various proxies for trigger events into their empirical default models, with varying degrees of success. For example, Deng et al. [1996] used a competing risk survival framework to model default and prepayment and included

[3]Asay [1979] was the first to apply the Black and Scholes methods to mortgage pricing. See Kau and Keenan (1995) for an overview of that literature.

[4]Campbell and Dietrich [1983] in a sample of privately insured mortgages (held by the Mortgage Guaranty Insurance Corporation) found that both income and unemployment rates were important determinants of mortgage default. Thibodeau and Vandell [1985], using data from a Savings & Loan association found similar results, and also found that wealth levels seemed to predict default. See Vandell [1995] for an overview of this early literature.

[5]He used a stochastic jump process to model the trigger event and was successful in replicating actual default behavior in simulations.

regional unemployment rates and divorce rates as proxies for trigger events. However, they concluded that regional unemployment was not an important factor in their model as the sign of the regional unemployment coefficient was mixed and statistically insignificant in several cases.[6] In contrast, other studies such as Deng et al. [2000] argued that unobserved heterogeneity such as job loss and divorce, are important determinants of mortgage default.

Coinciding with the mortgage default and foreclosure crisis that started in 2007, the literature on the determinants of mortgage default resumed in earnest. Due to the dramatic decline in house prices that precipitated the huge increase in defaults and foreclosures and the severe recession characterized by double-digit unemployment rates at the national level, the recent literature has focused on the roles of negative equity and unemployment in causing mortgage defaults. This literature was kicked off by Foote et al. [2008] who used mortgage data from Massachusetts in the early 1990s as well as in the early part of the recent financial crisis to assess the role of negative equity in the mortgage default decision. In line with their theoretical model, they found that the majority of people with negative equity do not default. They argued that the low default rates by homeowners likely reflected price expectations and that those who actually did default likely defaulted because of a double trigger event—negative equity and some adverse life event like job loss or health problems. In an attempt to capture these trigger effects, the authors used a local unemployment indicator, which has now become a standard in the literature.

Many interpreted this finding as evidence against the concept of widespread "strategic" or "ruthless" default—the idea that mortgage borrowers default solely based on the decline in the value of their property relative to their remaining mortgage balance—which is related to the predictions of the option-theoretic literature on mortgage default discussed above. This prompted numerous additional studies on the determinants of default and specifically on the importance of strategic default versus default due to trigger events, or as the literature refers to it as the "double-trigger" explanation of mortgage default.[7] For example, Bhutta et al. [2011] used data on non-agency, securitized mortgages and documented that default rates increase dramatically for borrowers in positions of severe negative equity. The authors interpreted these results as evidence that people only strategically default when there is considerable negative equity (-60% or lower), and posited that for more moderate levels of negative equity, the role of trigger events is likely important. Another highly cited study by Guiso et al. [2010] used a different approach to assess the importance of strategic default. The authors conducted a household survey that asked homeowners under what conditions they would strategically default on their mortgages. The study found that the most im-

[6]Capozza et al. [1997] also used regional unemployment and divorce rates to proxy for trigger events and found that they had little economic impact on default propensities.

[7]Double trigger refers to the combination of negative equity and job loss (or some other type of trigger like a divorce, death of a spouse, etc.)

portant driver of strategic default is severe negative equity, with race, gender, expectations about future employment, and views about fairness and morality also having importance.[8] Goodman et al. [2010] tried to disentangle the relative importance of negative equity and unemployment in driving defaults using data on non-agency securitized mortgages and unemployment rates at the county-level. The authors concluded that negative equity predicts default behaviour more so than regional unemployment, but explicitly discussed the limits of using a regional unemployment rate and the bias it might induce towards negative equity:

> "It is important to realize that we cannot tie the employment status of an individual loan to a particular borrower; we can only tie the unemployment rate of that MSA to a resident borrower. While we use a similar methodology to derive mark-to-market CLTV from original CLTV, the distortion is likely to be less dramatic for CLTVs. *That is, if the unemployment rate in a particular area is only 10%, a particular borrower is only 10% likely to be unemployed. However, if homes in a given area have depreciated by 40%, that borrowers house is likely to have dropped a relatively similar amount.*" (p. 4)

Recent work by Gyourko and Tracy [2013] seems to confirm this intuition. The authors show using simulations that empirical research attempting to uncover the relationship between unemployment shocks and mortgage defaults likely suffers from severe attenuation bias. That is, by aggregating unemployment (which is an extreme form of measurement error), and regressing the precise default status on the imprecise unemployment rate one introduces a downward bias in the estimate of the effect of unemployment on default. Thus, using local unemployment rates as proxies for individual unemployment shocks can result in severely underestimating the role of unemployment in the default decision. This could explain the tendency of many empirical default studies to find an insignificant role for unemployment, as discussed above.[9]

The attenuation bias illustrated in Gyourko and Tracy [2013] is a result of not observing employment status at the individual level. The datasets used in the existing literature have simply not contained such information, and as a result, researchers were forced to proxy for individual employment status with aggregate rates. This study is one of the first to incorporate information on individual unemployment spells in a model of mortgage defaults,

[8] While this paper contributed significantly to the literature and provided unique insights into strategic default, a major drawback of the study is the fact that it is a hypothetical survey, so that it is impossible to determine whether mortgage borrowers would actually behave in a manner that is consistent with their reported answers.

[9] There is a considerable amount of research in addition to the studies mentioned above, such as Mayer et al. [2009], and Haughwout et al. [2008], which also find that local unemployment rates are only weakly correlated with default rates.

and our findings regarding the importance of unemployment in causing default complements the Gyourko and Tracy [2013] study and suggests that their simulation exercise is accurate.

Another shortcoming of the datasets used in the existing empirical mortgage default literature is the lack of information regarding borrowers' overall financial situation. The level of a household's precautionary savings and liquid assets as well as illiquid assets, and the size of other debt payments may also factor into its decision to default.[10] Elul et al. [2010] is one of the only studies to our knowledge that used information on certain aspects of household balance sheets to predict mortgage default. The authors used credit bureau data from Equifax combined with loan-level mortgage data, and found that high credit card utilization rates (i.e. those who borrow up to their credit limits), large combined loan-to-value ratios (the first mortgage payment plus second mortgage payment divided by income) and negative equity are the most important factors in determining default. The authors also found that county-level unemployment rates have some predictive power, but less than high credit card utilization rates. We will refer to these findings as the illiquidity results, since people who borrow over their limits at punitive interest rates must necessarily be cash constrained.

While no U.S. studies of mortgage default have been able to incorporate individual unemployment shocks, there are a few studies that have done so using various European micro datasets. For example, Böheim and Taylor [2000] used the British Household Panel Survey (BHPS) to study the role of unemployment and financial stress in the decision to default. In contrast to the PSID data used in this study, the timing of the questions in the BHPS is similar to the SCF in which the degree of default over the past 12 months is reported but the date of default is not.[11] Böheim and Taylor [2000] find a similar ordinal relationship between negative equity and unemployment, with an unemployment coefficient roughly double the negative equity coefficient, but they stop short of looking at interactions.[12] Finally, Mocetti and Viviano [2013] used Italian annual tax records and unemployment records to look at the role of job loss in default. They found that job loss over the tax-year is a strong predictor of default, more so than changes in county-level home prices.

While these European-based empirical studies are important, none of them address the trigger hypotheses central to the negative equity policy debate. Moreover, our study exploits the precise timing in the PSID of unemployment and default questions as well as the survey-date measurements of wealth. By using a dataset with each of these variables, we are able to

[10] See the two-period model developed by Foote et al. [2008] for an example of how wealth could play an important role in the default decision.

[11] For example, the BHPS asks, "In the last twelve months have you ever found yourself more than two months behind with your rent/mortgage?"

[12] Gathergood [2009] conducted a similar analysis using the BHPS, except it focuses on the 5 years following an initial mortgage purchase. The study finds that burdensome credit payments, long term sickness, divorce, and negative equity are all better predictors of default than unemployment.

precisely test the drivers of mortgage default and test the relevance of trigger events versus stragic default based solely on the degree of negative equity.

2.1. Recent Advances in Theory

In the aftermath of the U.S. foreclosure crisis, there have also been advances in the theoretical mortgage default literature. Specifically, there have been attempts to integrate mortgage default into more general, equilibrium models of consumer behavior in order to study the interplay between the mortgage default decision and various aspects of consumption portfolio choice. These studies have focused on foreclosure, and not necessarily default.[13] In this section we briefly describe the main findings of this literature, which guide some of our variable choices in the empirical analysis below.

In a partial equilibrium setting, Campbell and Cocco [2011] modeled mortgage foreclosure structurally and found that: (i) negative equity alone; (ii) borrowing constraints in combination with negative equity; (iii) high debt to income ratios in combination with negative equity; (iv) remaining term and type of mortgage in combination with negative equity; and (v) expected income growth rates are all important determinants of foreclosure. In Garriga and Schlagenhauf [2009], negative equity alone is never the lone cause of foreclosure. Households decide to sell for some reason other than equity, typically a decline in income in combination with low savings, because equity is only realized after the house is on the market. Thus every default is necessarily a double-trigger default.

Corbae and Quintin [2009] focused on housing stock shocks which are two-for-one shocks, reducing equity and the flow utility from housing. In equilibrium, there are only 'strategic' foreclosures in the sense that the housing stock shock induces default, but the homeowner could still afford to make the payments. In the case where there is positive equity and the mortgagor has experienced a series of bad income shocks and cannot afford the payments, the mortgagor simply sells the property. Both Garriga and Schlagenhauf [2009] and Corbae and Quintin [2009] found roles for mortgage innovation on foreclosure rates via increased susceptibility to negative equity.[14]

Foote et al. [2008] used a much simpler, two-period model to show that households choose to default and lose their homes to foreclosure if the net implicit rents from owning plus the *expected* net equity position over their tenure horizon is positive.[15] In fact, the contempo-

[13]Foreclosure is quite unique from default in the sense that lenders initiate the foreclosure process only after a borrower chooses to default. Foote et al. [2008] argue that negative equity is a necessary condition for foreclosure to occur, but Herkenhoff and Ohanian [2012a] show that negative equity is not a necessary condition for default.

[14]Both Hatchondo et al. [2012] and Corbae and Quintin [2009] also argued that recourse laws increase defaults.

[15]In their model there is no distinction between default and foreclosure

raneous value of equity does not factor into the default/foreclosure decision in the model. In sum, they find that expected house price appreciation, the flow utility from owning, and the mortgage payment size are the main factors in determining whether or not a household chooses to default and experience foreclosure.

Herkenhoff and Ohanian [2012b] is the only existing model that includes both mortgage default and foreclosure. Based on the relationship between employment and mortgage default in the PSID, they build a high-frequency model with three partial equilibrium markets: (i) a labor market, (ii) an asset market, and (iii) a mortgage market. In this framework, they find that job loss and unemployment benefit expiration are the main causes of default. Moreover, they find that the strength of these factors is nearly independent of equity status, a direct implication of their calibration strategy. Since they calibrate the flow utility from housing to match observed large defaulter cure rates, the resulting flow utility from housing dwarfs the role of negative equity. In other words, every default is involuntary and occurs because of job loss induced liquidity constraints or benefit-expiration induced liquidity constraints.

3. PSID Data

The primary data used in this study come from the 2009 PSID Supplement on Housing, Mortgage Distress, and Wealth Data. The 2009 PSID survey was divided into 12 sub-waves, and was conducted over the course of the year. There were 8,690 households surveyed in the 2009 PSID, however in the empirical analysis we impose a few restrictions that reduces the sample size. In particular, we eliminate from our sample disabled households and households that are not of working-age (younger than 24 or older than 65), which reduces the sample to 6,820 households. In addition, we eliminate renters as well as households that are homeowners but who report not having a mortgage, which further reduces the sample to 3,037 households. Finally, in our regression analysis below we only include households whose head reports being in the labor force.

Our analysis focuses on the determinants of mortgage default, and specifically on the role of negative equity, unemployment, and wealth status. In the next section we describe the key PSID variables in the analysis.

3.1. PSID Variable Definitions and Summary Statistics

The top panel of Table 1 displays summary statistics of demographic characteristics of the households in our estimation sample. Statistics are provided for all households in the sample as well as the sample of households that have defaulted on their respective mortgages. In this section we will focus on summary statistics for all households, and postpone a discussion of the corresponding statistics for defaulters until section 4.

The average age of the household heads in our sample is approximately 44 years, and as mentioned above, we restrict the sample to households with a head between the ages of 24 and 65 years. Approximately 85% of the household heads in our sample are male, 72% are white, and 22% are black. The majority of households are married (73%) and the majority of household heads (about 58%) have at least some college education, which is not surprising given that we are restricting the sample to homeowners.

The bottom panel of Table 1 displays summary statistics regarding the financial situation of the households in our sample at the time of the survey. Specifically the table contains information on the distribution of total household income, liquid and illiquid assets, unsecured debt, and outstanding hospital bills. We present summary statistics for both variable levels and ratios with respect to income. In some of the empirical models below we specify these variables as sets of indicators, and thus we include summary statistics for the indicator variables as well in the table. Average household income is approximately \$110 thousand in our sample of homeowners with a mortgage. Households hold \$18 thousand in liquid assets and \$110 thousand in illiquid assets on average,[16] and report, on average, approximately \$16 thousand in unsecured debt and about \$900 in outstanding hospital bills.[17] Finally, almost 6% of households report having declared bankruptcy before 1995.[18]

The top panel of Table 1 also contains summary statistics regarding mortgage delinquency, unemployment, and negative equity. Households were asked how many months they were behind on their mortgage payments at the time of the PSID interview.[19] Approximately 6.5% were at least one month behind (30+ days delinquent), while 3.9% were at least two months behind (60+ days delinquent). In the remainder of the paper we will adopt the definition of default that corresponds to two or more payments behind (i.e. at least 60+ days delinquent), as this is the convention in the literature. The 30+ day and 60+ day delinquency rates that we calculate in the PSID are lower than delinquency rates in the broader U.S. population according to various sources (see Table 13 in Appendix A for more details). The Board of Governors, for example, publishes delinquency rates among FDIC insured banks, and they report an average 30+ day delinquency rate of 9.1% averaged over 2009. According to the National Delinquency Survey conducted by the Mortgage Bankers Association (MBA), the average 30+ day delinquency rate in 2009 was 9.4%, while the aver-

[16]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.

[17]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.

[18]1995 is the most recent PSID survey to collect bankruptcy information.

[19]In Appendix A we provide the exact PSID survey question on mortgage delinquency.

age 60+ day delinquency rate was 5.8%. One possible explanation for the lower delinquency rates in the PSID is an under-representation of subprime mortgages. The subprime segment of the market drove mortgage default rates in the crisis period (for example, according to the MBA, the average 30+ day delinquency rate for subprime mortgages in 2009 was 25.5%). There is some indirect evidence of the under-representation of subprime mortgages in our sample. The majority of subprime mortgages originated before the crisis carried an adjustable interest rate (according to the MBA, 67% of subprime originations in the first half of 2006 were adjustable rate mortgages)[20], and in our sample, only 9.1% of loans are ARMs (see the bottom panel of Table 1).

In our sample 7% of households report being unemployed, while 3.6% report having lost their job within 6 months of the date of the interview. Unfortunately, the mortgagor unemployment rate in the PSID is not readily comparable to any other national unemployment rate. However, we note that the mortgagor unemployment rate is lower than the headline BLS unemployment rate for ages 16+, which was 9.3% averaged over 2009.[21]

12.6% of the households in the sample are in a position of negative equity. We construct the negative equity variable using the reported home value (HV) less the reported first mortgage principal balance outstanding (PR_1) and the reported second mortgage principal outstanding (PR_2). Keeping with the literature, we express equity as one minus the combined loan-to-value ratio (CLTV):

$$Equity = 1 - CLTV = 1 - \frac{PR_1 + PR_2}{HV}, \tag{1}$$

although in our estimation below we use CLTV itself.

The top panel of Figure 1 displays the distribution of equity in our sample, while the bottom panel shows the equity distribution estimated by Corelogic in the third quarter of 2009. [22] Although the shapes of the equity distributions are quite similar across datasets, the level of overall negative equity reported by Corelogic is approximately twice as high as it is in our PSID sample. According to Corelogic, slightly more than 10% of properties had greater than 25% negative equity, while slightly less than 4% do so in the PSID. While there

[20]See `http://www.mortgagebankers.org/NewsandMedia/PressCenter/46043.htm` for the October 2006 press release.

[21]The overall unemployment rate in the 2009 PSID for ages 16+ is 13.7%, which is significantly higher than the BLS figure.

[22]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 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.

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% to 10% (see Benítez-Silva et al. [2008]). Thus, a self-reported CLTV ratio of 90% is on the verge of realizing negative equity in the event of a sale.

While the PSID clearly seems to understate 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 have 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 who believe that they are in positions of negative equity are given negative equity, and this is the group of households whom we expect to be most sensitive to negative equity in terms of their default behavior.[23]

Figure 2 displays unconditional default rates across the equity distribution in our PSID sample. The non-linear relationship between equity and default that has been documented in the literature (Foote et al. [2008]) is apparent. The default rate associated with households with equity values above -5% is between 2% and 3%. However, the default rate increases significantly for equity values below -5%, reaching more than 25% for households with equity below -25%. This pattern is often interpreted as evidence of strategic default, and we will come back to this issue in our analysis below. To capture the non-linear relationship between equity and default in our empirical analysis and to maintain consistency with the previous literature, we use indicator variables for different levels of the CLTV ratio.

Finally, Table 1 also displays summary statistics of certain mortgage terms of interest. In our empirical analysis below, we control for various mortgage characteristics including the type of mortgage, 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.[24] In addition, we control for whether the state of residence allows lender recourse, whether the state is characterized by a judicial foreclosure process (as opposed to power-of-sale), and whether the state of residence is AZ, CA, FL, or NV, which are often to referred to as the "sand states."[25]

[23]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.

[24]An oft forgotten facet of real estate law is the only purchase money mortgages (i.e. mortgages used to buy a home directly) are non-recourse loans, whereas refinanced mortgages (which are mortgages taken out to pay off another mortgage) are typically treated as recourse loans. Therefore, it is more important to control for the refinance status than for the recourse status of a state.

[25]Ghent and Kudlyak [2011] provide evidence that default rates are higher in states that do not allow lender recourse. Gerardi et al. [2011] find that at any given point in time, default rates are higher in judicial states compared to power-of-sale states.

Finally, we add controls for recent house price appreciation (HPA) at the state-level (using house price indices estimated by the Federal Housing Finance Administration (FHFA)), to capture household-level expectations of future house price movements to the extent that households form expectations in an adaptive manner, and also recent growth in the state-level unemployment rate. We use the growth rate in state-level house prices and unemployment rates from 2008 to 2009, but our results are similar if we use growth rates from 2006 to 2009 or 2007 to 2009.

4. Results

In this section we present results on the importance of various default triggers in the PSID. We begin by describing the characteristics of PSID households in default and then present results from our empirical models. In Appendix B we also conduct a parallel analysis using data from the 2007 and 2009 Survey of Consumer Finances (SCF), in order to externally validate the results from the PSID analysis. The results from the SCF data are broadly consistent with the PSID results.[26]

4.1. Characterizing Defaulters

Our first set of results is a descriptive characterization of defaulters in the PSID. 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. Table 1 provides a comparison of the average mortgagor (including all mortgage observations) and the average defaulter (only those 60+ days delinquent as of the survey date) within our restricted mortgagor sample. Most notably, defaulters have an unemployment rate of 25% as compared to the average mortgagor who has an unemployment rate of 7%. This strong correlation between unemployment and default persists in every model that we consider below, regardless of the breadth of controls. Defaulters are also significantly different along many demographic margins. For example, only 17% of defaulters attained a college degree versus 32% of all mortgagors, and 58% of households that default are married compared to 73% of all mortgagors. Furthermore, defaulters are relatively low-income households with a mean income in 2009 of almost $40,000 less than the average mortgagor, and are also more than three times likely to have suffered a severe income loss of -50% or worse.

In terms of mortgage characteristics, 28% of defaulters have negative equity of -20% or worse versus 4% of all mortgagors. As we will see below, this correlation between severe

[26]Appendix A includes details of the questions used as well as a discussion about weighting.

negative equity and default also persists with the addition of various controls. The mortgage product mix is also skewed with 33% of defaulters reporting adjustable rate mortgages (ARMs) versus 9% of all mortgagors. The defaulters have much higher mortgage debt-to-income (DTI) ratios, reflecting their lower incomes as well as their larger remaining principal balances.[27] Defaulters have, on average, $60,000 more in outstanding mortgage debt and live in states that experienced a larger drop in home prices over the previous year. Geographically, 33% of defaulters reside in the sand states of AZ, CA, FL, and NV, whereas only 15% of all mortgagors reside in these states.

As mentioned above, the PSID is unique in providing household-level balance sheet data and mortgage repayment information. Table 1 shows that households in default have much larger unsecured debt positions, roughly $12,000 more in unsecured debts compared to the average mortgagor, and defaulters have almost $6,600 less in terms of net auto assets. Defaulters have significantly less business assets, and less "other housing" assets which include second residences, vacation homes, and investment properties. Defaulters have almost zero retirement savings ($800 on average) and approximately $15,000 less in liquid assets than the average mortgagor (liquid assets include checking and savings accounts, money market funds, certificates of deposit, government savings bonds, or Treasury bills). Defaulters also have almost $12,000 less in stock holdings than the average mortgagor.

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 unobservables in most loan-level data sets. To further exploit the unique nature of this data, in Section 5 we will use this information to conduct a descriptive analysis of strategic default in the PSID.

4.2. Suggestive Evidence of Double Trigger Events

Table 2 contains information regarding the double trigger event of job loss and negative equity as well as other types of financial shocks and negative equity. The table contains a comparison of default rates for various categories of borrower income and financial characteristics, stratified by whether a borrower has negative equity or positive equity and also whether a borrower has severe negative equity ($CLTV \geq 120\%$) or not. The table shows that unemployed households in the PSID with negative equity have an unconditional default rate of 30.0%, whereas employed households with negative equity have an unconditional default rate of 10.2%, which means that unemployment produces a difference in default rates of 19.8% among those with negative equity. In contrast, an unemployed household with positive equity has a 10.6% default rate, whereas an employed household with positive equity

[27]The DTI ratio is simply the ratio of the household's reported annual mortgage payment to its reported annual income.

has a 2.1% default rate, which means that unemployment produces a difference of 8.5% in default rates among those with positive equity. The simple interaction effect between unemployment *and* negative equity on the default rate is therefore 11.3% (= 19.8% - 8.5%), which implies that the double trigger effect of job loss and negative equity is to increase the default rate by 11.3% over and above either trigger on its own (i.e. this is the differential effect on the default rate induced by a unemployment shock among those with negative equity versus those with positive equity).

Likewise, unemployed households with severe negative equity have an unconditional default rate of 41.7%, whereas employed households with negative equity have an unconditional default rate of 22.5%, a difference of 19.2%. Unemployed households with non-severe negative equity have an unconditional default rate of 12.0%, whereas employed households with non-severe negative equity have an unconditional default rate of 2.3%, a difference of 9.7%. Thus the simple interaction effect between severe negative equity and unemployment is to raise the default rate by 9.5% (= 19.2% - 9.7%) over and above either trigger on its own.

A similar pattern holds among those with a liquid asset to income ratio less than 5%. The simple interaction between low liquid assets and negative equity is quite large at 5.7% (=(15.2%-5.7%)-(4.6%-.8%)). We also see the same type of result for DTI ratios, as well as income loss (calculated between 2007 and 2009). Unfortunately, the sample size used to compute each of these default rates is relatively small which makes it difficult to obtain power in any formal test of interaction effects with controls. Nonetheless, we attempt such tests below.

4.3. Unemployment and Default

The top panel of Table 3 illustrates the basic relationship between unemployment, recent job loss, and default using both a linear probability model (LPM) and a logit model. The first column shows the results from a simple unconditional regression of default (defined as 60+ days delinquent) on an indicator variable for being unemployed at the time of the PSID interview. The coefficient estimate implies that unemployed households are about 11 percentage points more likely to default compared to employed households. This is a huge effect, considering the fact that the default rate across all households in our sample is only 3.9%. The corresponding logit regression (column 4) produces an identical average marginal effect.[28] Columns (2) and (5) add an indicator variable of recent job loss (within 6 months of the interview). Households that are unemployed, but who have experienced a relatively

[28]For dummy variables, evaluation of the logit at the mean produces meaningless results, i.e. $P(Y = 1 \mid Z = 1 \cap X = \bar{X}) - P(Y = 1 \mid Z = 0 \cap X = \bar{X})$ makes little sense when X is an indicator and $\bar{X}$ is the average in the population of that indicator. Instead, we report average marginal effects which is averaging the marginal effect over individuals evaluated at their actual value of $X = X_i$ for each $i \in \{1, \cdots, N\}$. Thus

recent job loss are less likely to default compared to households who have been unemployed for longer period of time, however this effect is not statistically significant in either the LPM or logit models.[29]

Finally, columns (3) and (6) add demographic controls along with some state-level controls.[30] The estimates associated with the unemployment variables do not significantly change. There are a few notable patterns among the controls. Default rates among black households are approximately 3 percentage points higher than default rates among white households. Households with at least a college degree have lower default rates than households that did not graduate from high school (about 3 - 5 percentage points). Households living in states that experienced higher rates of house price appreciation in the previous year are significantly less likely to be in default. A one standard deviation increase in HPA (about 7%) is associated with a 3 percentage point decrease in the probability of default. Finally, we find a weak correlation between state-level changes in unemployment rates and default rates, which is consistent with the previous literature. In particular, the finding that individual unemployment status is strongly correlated with default while aggregated unemployment rates are not confirms the findings in Gyourko and Tracy [2013].[31]

4.4. Equity and Default

The bottom panel of Table 3 illustrates the basic relationship between equity and default in our PSID sample. In column (1) we display the estimate from a simple unconditional LPM of default on CLTV expressed as a decimal (i.e. a value of 0.9 is a CLTV of 90%), and in column (4) we display the average marginal effect from an unconditional logit model.

we report the average marginal treatment effect of Z (negative equity, job loss, etc.) on outcome Y (default):

$$AME(Z) = \sum_i (P(Y = 1 \mid Z = 1 \cap X = X_i) - P(Y = 1 \mid Z = 0 \cap X = X_i))/N$$

[29]According to the LPM estimates, a household that has been unemployed for less than 6 months is approximately 8 percentage points more likely to default compared to an employed household, while a household that has been unemployed for more than 6 months is almost 14 percentage points more likely to default. These results are consistent with the predictions of the model in Herkenhoff and Ohanian [2012b] in which the long term unemployed are the most likely to be liquidity constrained and default on mortgage payments. However, the difference between long-term and short-term unemployment in Table 3 are not statistically significant, and the magnitudes are sensitive to the particular model used in the estimation

[30]Specifically, we add a 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 measures state-level house price growth from 2008-2009 and the change in the state-level unemployment rate over the same period. For space considerations we only show the estimates associated with the statistically significant control variables.

[31]Taking out individual employment status does not materially affect the correlation between aggregate unemployment rates and default.

The CLTV coefficient estimate from the LPM implies that a one-standard deviation increase in CLTV (approximately 35 percentage points) is associated with a 4.6 (=.132*.35*100) percentage point increase in the probability of default.

We know from Figure 2 that the relationship between equity and default is highly non-linear, so in columns (2) and (5) we specify CLTV in terms of a series of indicator variables with the baseline case corresponding to households with CLTV $<$ 70%. The results are consistent with the pattern observed in Figure 2. There is a positive correlation between CLTV and default that becomes stronger with higher CLTV values (greater negative equity positions). Households with CLTVs between 100% and 120% (negative equity up to -20%) have default rates that are 3.4 percentage points higher than households with CLTVs less than 70%, ceteris paribus. But even more striking is the finding that households with CLTVs above 120% (negative equity worse than -20%) are 22.6 percentage points more likely to default as compared to their counterparts with CLTVs less than 70%. The corresponding default probability in the logit specification is 10 percentage points. Columns (3) and (6) include our demographic and state-level controls. The coefficient magnitudes associated with the higher CLTV ranges slightly decrease, but otherwise the results do not significantly change.

It is clear from Figure 2 and Table 3 that default rates are significantly higher for households in positions of negative equity or near-negative equity (i.e. CLTVs above 90%), than for households with significantly positive equity, which is completely consistent with findings in the existing literature. As a result, in the remainder of our analysis we will focus on negative equity as a trigger for mortgage default. In addition to focusing on the exact negative equity threshold (i.e. CLTV=100%), we will also look at alternative thresholds of CLTV=90% and CLTV=120%. Moving costs and realtor fees could easily add up to 10% of the property value, so that a household that needs to sell could effectively have negative equity even with a CLTV as low as 90%. Prior research has found significantly higher default rates for households in positions of deep negative equity (as we also find in Table 3) versus only moderate negative equity, so that a threshold of 120% will allow us to focus on these households.[32]

4.5. Trigger Analysis: Unemployment and Negative Equity

Having established that both unemployment and negative equity are important determinants of household-level default behavior on their own, we now estimate models with both variables included to determine the relative strength of each predictor. In Table 4 we report estimation

[32]Prior studies like Bhutta et al. [2011] have considered even higher negative equity thresholds like CLTV=150%. However, we simply do not have enough observations in the PSID with such deep negative equity values to be able to obtain any degree of precision with such a high threshold.

results from LPM and logit models that include both variables. We include the same set of demographic and state covariates, and add a set of mortgage characteristics to the set of control variables. These include an indicator for a second mortgage, an indicator for whether the first mortgage is a refinance loan, an indicator for whether the first mortgage is an ARM or a FRM, the current interest rate associated with the first mortgage, and an indicator for whether the maturity of the first mortgage is greater than 15 years.[33]

The estimates from the LPM reported in columns 1-3 in Table 4 indicate that long term unemployment is more strongly correlated with default compared to the lower negative equity thresholds of CLTV=90% and and CLTV=100%. However, the CLTV=120% threshold is a stronger predictor of default in the LPM, as households with CLTV≥120% are almost 18 percentage points more likely to default than borrowers with CLV¡120%. This is not the case in the logit model however, The estimated marginal effects from the logit (columns 4 - 6), suggest that households who have been unemployed for more than 6 months are approximately 9 to 10 percentage points more likely to default compared to employed households. In contrast, households with negative equity or near negative equity (CLTV≥100 and CLTV≥90, respectively) are approximately 4 percentage points more likely to default than households with positive equity, while households with deeper negative equity (CLTV≥120) are about 6 percentage points more likely to default. Thus, according to the logit results, long-term unemployment is a slightly stronger default trigger than negative equity. Given, the well-documented econometric issues with the LPM,[34] we place more weight on the logit results, and thus conclude that while unemployment and negative equity are both important triggers of default, unemployment appears to be the stronger of the two.

4.6. Other Triggers

As mentioned above, previous studies in the empirical mortgage default literature have found some evidence that other triggers, such as divorce, death of a spouse, adverse medical shocks, and negative income shocks, in general, are correlated with default. Of course these studies did not have information on household-level shocks, and instead were forced to use aggregate proxies, such as divorce rates at the county-level. The PSID contains information on divorce and medical shocks at the household-level, which we can use to test their importance as triggers of mortgage default.

[33] In all of the empirical models we also include a set of indicator variables to deal with missing observations. For discrete variables, we simply add an indicator to the model that takes the value of one if the observation has a missing value and zero otherwise. For continuous variables, we add such an indicator to the model and set the value of the continuous variable to zero. We do not report the estimates associated with these variables for space considerations.

[34] One important drawback of the LPM is the fact that it does not restrict fitted probabilities to lie within the unit interval

We identify heads of households that either went through a divorce or lost a spouse between the 2007 and 2009 PSID surveys.[35] In addition, we use information on outstanding hospital bills to proxy for an adverse medical shock. We construct an indicator variable to identify households that have outstanding hospital bills in excess of 10% of annual income.[36] Finally, we also construct a negative income shock trigger using information on income from the 2007 PSID survey. We calculate the percentage change in reported total household income between the 2007 and 2009 surveys, and form indicator variables for households in the bottom 25th percentile of the distribution of income growth (approximately a -10% change or worse) and households in the bottom 5th percentile of the distribution of income growth (approximately a -50% change or worse).

Table 5 reports results on the importance of these additional potential triggers. In the top panel of the table we consider the more moderate income shock trigger of -10% or worse, while in the bottom panel we consider the more extreme income trigger of -50% or worse. Divorce or loss of spouse does not appear to be an important determinant of mortgage default in our PSID sample.[37] The point estimates from the LPMs and logits are small and not statistically different from zero. There is slightly more evidence in support of adverse medical shocks as a default trigger, but that evidence is only weak at best. The point estimates associated with the hospital bill indicator are relatively large (between 5 and 7 percentage points depending on the model and negative equity specification), but they are rarely statistically significant at the 10 percent level.

There is evidence that negative income shocks serve as default triggers, especially severe income shocks. According to the top panel of the table, households that experienced at least a 10% drop in income were between 2.4 and 3.1 percentage points less likely to default compared to households that experienced a rise in income or a less severe drop. Households that experienced at least a 50% drop in income were between 7.2 and 9.3 percentage points less likely to default. This effect is larger than most of the negative equity triggers. It is a little surprising that the inclusion of these income shock indicators has little effect on the magnitude of the correlation between unemployment and default. Thus, it is not the case

[35]Specifically we consider a divorce to have taken place if the head of household reported being married in the 2007 survey and divorced or separated in the 2009 survey, and we consider a death of a spouse to have taken place if the head of household reported being married in the 2007 survey and being a widower in the 2009 survey.

[36]Approximately 1.8% of households in our sample report outstanding hospital and nursing home bills in excess of 10% of income. Thus, this variable captures the few households in the PSID that have been hit with severe medical issues. We also tried using the level of hospital bills outstanding, and this variable had essentially zero correlation with mortgage default.

[37]The difference in sample sizes between columns (1)-(3) and columns (4)-(6) is due to the fact that a missing divorce indicator perfectly predicts non-default. These 59 missing values are not correlated with any observables, and are thus dropped to provide for well-defined coefficients in the logit MLE estimations. The point estimates in the linear probability model are unaffected by the inclusion of these observations.

that the income shock indicators are simply picking up the income loss associated with job loss.

4.7. Wealth and Prior Bankruptcy

Previous studies in the literature have stressed the potential importance of wealth in a household's decision to default on a mortgage.[38] We have information regarding assets and liabilities in the PSID, but we only have that information at the time of the survey date. Thus, we cannot make any causal inference regarding the relationship between wealth and default. For example, a negative correlation between wealth and default could be causal in the sense that a negative wealth shock (such as a fall in the stock market, or failed business venture) leads directly to default. However it could simply be the result of other shocks, such as an unemployment shock leading a household to draw down savings and increase unsecured debt in an effort to put off default for as long as possible. We cannot distinguish between those two scenarios with our PSID data. With this caveat in mind, in this section we will characterize the relationship between the likelihood of mortgage default and asset and debt positions. We focus on three variables in particular: the ratio of liquid assets to income, the ratio of illiquid assets to income, and the ratio of unsecured debt to income.

Table 6 displays estimation results, where the wealth variables are each expressed as a series of indicator variables to capture potential nonlinearities in the relationship between the variables and mortgage default. The estimates suggest that households with extremely low levels of liquid and illiquid assets (less than 5% of income) are the most likely to default. The evidence is stronger for liquid assets, as most of the illiquid asset indicator variables are not statistically different from zero. Households with a liquid asset to income ratio of less than 5% are between 3 and 8 percentage points less likely to default compared to households with ratios of more than 50%. There is also evidence that households with extremely high levels of unsecured debt (over 50% of income) are much more likely to default compared to households with moderate-to-very low levels of unsecured debt. For example, households with outstanding debt levels above 50% of income, on average, default approximately 2.6 to 5.1 percentage points more often than households with debt levels below 5% of income.

It is also noteworthy that the estimated marginal effects associated with the unemployment indicator in the logit models decrease with the addition of these wealth variables (this is not the case in the LPMs). If we compare the estimates in Table 6 to the estimates in Table 5, the unemployment marginal effects decrease by about 50%, while the negative equity marginal effects are largely unaffected. This is consistent with our story above, in which households that lose their jobs run down their assets and increase their debt levels before

[38] For example, see the discussion and model in Gerardi et al. [2007].

finally defaulting. If this were the case, then we would expect that adding wealth variables into the default regression would take away some of the explanatory power of unemployment, which is exactly what we observe.

The literature has consistently found that prior credit history is an important determinant of mortgage default. Information regarding credit scores is not available in the PSID, but there is a limited amount of information regarding previous bankruptcy declarations. Specifically, households were asked in the 1996 PSID survey whether they had ever declared bankruptcy, and thus, we have information on household bankruptcies that took place before 1996.[39] Panel A of Table 7 shows that surprisingly, almost 6% of the PSID sample declared bankruptcy prior to 1996. There is some debate regarding the information content of previous negative credit events like bankruptcy in the literature. According to federal law, bankruptcies must be removed from credit reports after 10 years, so that pre-1996 bankruptcies would not have shown up on credit reports at the time of the 2009 PSID survey. Musto [2004] argues that this information loss has important implications for the market:

> "Federal law mandates the removal of personal bankruptcies from credit reports after 10 years. The removal's effect is market efficiency in reverse. The short term effect is a spurious boost in apparent creditworthiness, especially for the more creditworthy bankrupts, delivering a substantial increase in both credit scores and the number and aggregate limit of bank cards. The longer term effect is lower scores and higher delinquency than initial full information scores predict. These findings relate to both the debate over the bankruptcy code and the wisdom of influencing market clearing by removing information."

The bottom panel of Table 7 shows the unconditional default rate for the households that previously declared bankruptcy and the households that did not. In contrast to Musto [2004]'s assertion, default rates are actually 1 percentage point lower among the households that declared bankruptcy prior to 1996. To ensure that this relationship is robust, we include a pre-1996 bankruptcy indicator into the LPMs and logit models estimated in Table 2. The results are displayed in Table 8, and are consistent with the unconditional results. We find no evidence of a positive correlation between prior bankruptcy declarations and mortgage default.

4.8. Double Triggers

We now turn to a test of what we will call the "double trigger hypothesis," or the DTH. The idea of the DTH is that the *combination* of job loss and negative equity is instrumental in

[39] The PSID did not ask questions about bankruptcy after 1996.

driving mortgage defaults, as opposed to unemployment or negative equity by themselves. We will measure the importance of the DTH using the following estimated statistic:

$$\left[P(D=1 \mid I_{\{Neg.\ Eq.\}}=\mathbf{1} \cap I_{\{Unemploy\ 2009\}}=\mathbf{1}) - P(D=1 \mid I_{\{Neg.\ Eq.\}}=\mathbf{1} \cap I_{\{Unemploy\ 2009\}}=\mathbf{0})\right]$$
$$-\left[P(D=1 \mid I_{\{Neg.\ Eq.\}}=\mathbf{0} \cap I_{\{Unemploy\ 2009\}}=\mathbf{1}) - P(D=1 \mid I_{\{Neg.\ Eq.\}}=\mathbf{0} \cap I_{\{Unemploy\ 2009\}}=\mathbf{0})\right]$$

This is the additional effect of unemployment on default for those with negative equity versus those with positive equity.[40] In the LPM, this statistic corresponds exactly to the estimated coefficient on an unemployment and negative equity interaction term. In the logit model, this statistic is slightly more complicated to compute due to the inherent non-linearity of the model.

Table 9 displays estimation results for the unemployment and negative equity interaction term. For ease of interpretation, we do not distinguish between short and long term unemployment spells (i.e. we leave out the indicator for job loss within the previous 6 months). There is some evidence of a double trigger effect, but it is very sensitive to the negative equity threshold. The interaction term is large and statistically significant for the CLTV>90 threshold in the LPM (at the 5% significance level), but is not statistically significant in the logit. The combination of near-negative equity and unemployment increases the probability of default by over 14 percentage points in the LPM and almost 8 percentage points in the logit. This is a huge effect considering the fact that the unconditional default rate in the data is only 3.5 percentage points. However, for the other negative equity thresholds, the estimated interactions are smaller in magnitude and not statistically different from zero. The lack of statistical significance could be due to the small PSID sample, as we only have 13 households that are unemployed with CLTV>90%, 9 unemployed households with CLTV>100%, and 5 unemployed households with CLTV>120%. Thus, in general we conclude that there is mixed evidence regarding the importance of the double trigger of unemployment and negative equity. For near-negative equity and moderate negative equity the interaction appears to be quite important (at least in the LPMs), and quantitatively more important than negative equity as a default trigger by itself. However, for households with severe negative equity, negative equity is a very important trigger by itself, and the interaction with unemployment does not appear to be very important.

[40] This is exactly equivalent to the additional effect of negative equity for those who are unemployed versus those that are employed.

5. Evidence for Strategic Default

The concept of strategic default has been a topic of much debate in the commentary on the U.S. mortgage and foreclosure crisis. There have been a significant number of anecdotal stories, mostly in newspaper articles, about individuals who stop paying their mortgages and walk away from their homes due to severe negative equity, despite the financial capability of continuing to make payments.[41] In addition, there are a few academic studies that claim to indirectly identify strategic default. For example, Guiso et al. [2010] find evidence from a survey that many homeowners would be willing to strategically default under certain conditions. Bhutta et al. [2011] find a strong correlation between severe negative equity (-60% or worse) and default among non-agency securitized mortgages, and interpret it as evidence of the importance of strategic default.

There are at least two difficult issues that must be confronted in an analysis of strategic default. First, one must define exactly what a strategic default is, which is not so straightforward, and second, one needs detailed data on both mortgage payment histories as well as information on income and wealth. There is no consensus on a single, coherent definition, and economic theory provides little guidance, as in the context of an optimization problem, all mortgage defaults are to some degree "strategic." We believe that what most commentators mean by the term strategic default is the decision by a borrower to stop making payments despite the financial ability to continue to do so at little cost. By little cost, we mean that a borrow has enough liquid savings or a large, stable source of income to meet monthly mortgage obligations without having to borrow at high interest rates and/or make a considerable sacrifice in terms of current consumption. While this is by no means a precise definition, our goal in this section is not to identify behavior that can unambiguously be characterized as evidence of strategic default, but rather to describe the basic patterns of wealth holdings for borrowers that choose to default and let the reader draw his or her own conclusions about what can be inferred about strategic default. In terms of data, while the PSID is certainly not a perfect dataset to study aspects of strategic default, it does contain information on both mortgage default and wealth holdings, which is not the case in virtually all administrative loan-level datasets.

Table 10 shows the reported wealth holdings of households that were at least 60-days delinquent on their mortgages at the time of the 2009 PSID survey. We focus on liquid assets (defined above) as well as less liquid forms of wealth such as stock and bond holdings and retirement account assets, as well as unsecured debt. The table shows the distribution of assets and debt across all households that default (Panel A), households that default with negative equity (Panel B), and households that default with severe negative equity

[41] See for instance the WSJ article entitled "American Dream 2: Default, Then Rent," by Mike Whitehouse.

(Panel C). Since the entire concept of strategic default is based on increasing net worth by eliminating negative equity, we will focus on households that default with negative equity, but we add a panel for all defaulters for comparison purposes. It is clear from the table that the vast majority of negative equity defaulters have extremely low levels of liquid and illiquid assets. Three-quarters of severe negative equity defaulters have less than $2k in liquid assets and 90% have less than $10k in liquid assets. In addition, 90% of severe negative equity defaulters have zero holdings of stocks, bonds, and retirement account assets. A significant number of these households have non-trivial values of outstanding unsecured debt. Half of negative equity defaulters have over $10k of unsecured debt, while half of severe negative equity defaulters have over $4k of unsecured debt.

Finally, in each panel of Table 10 we display the distribution of the ratio of liquid assets to the monthly mortgage payment and the ratio of illiquid assets (defined to include stocks, bonds, and retirement accounts) to the monthly mortgage payment. Almost three-quarters of negative equity defaulters do not have enough liquid assets to make a single mortgage payment, while three-quarters of severe negative equity defaulters do not have enough liquid assets to make two payments. At the bottom of each panel we show the number and fraction of households in default that have a liquid asset-to-payment ratio *or* an illiquid asset-to-payment ratio greater than 1, 2, 6, and 12. According to the table, over 60% of severe negative equity defaulters report having neither enough liquid assets or illiquid assets to make one month's mortgage payment. It is unlikely that these households would qualify as strategic defaulters under virtually any definition, and thus we interpret 40% as an upper bound for potential strategic defaults in the PSID among those with severe negative equity. In contrast, approximately 13% of severe negative equity defaulters report having liquid or illiquid asset holdings greater than 12 months worth of mortgage payments. One could make the case that these borrowers fit a reasonable definition of strategic default in the sense that even without factoring in income, they have enough assets to continue making mortgage payments for at least one year, but choose to default instead.

Let us step back and broaden the scope of our analysis to include all delinquent mortgagors (not just those with severe negative equity). Among *all* defaulters, only 13.9% (=16/115) have negative equity (CLTV>100%) and enough liquid or illiquid assets to make 1 payment. That is, only 13.9% of all defaulters are underwater and would be able to make one month's mortgage payment out of their savings and financial wealth (a result that echoes Gruber [2001]).

5.1. Strategic Default in the SCF

Table 11, which is based on the SCF, confirms the PSID patterns illustrated in Table 10: a large fraction of defaulters have insufficient liquid assets to cover 1 month's mortgage payment, especially those with severe negative equity. In the SCF, we measure liquid assets as the sum of savings, checking accounts, and CDs. Since the SCF collects detailed account information, Table 12 computes liquid assets to mortgage payment ratios excluding CDs.

In the first panel of Table 11, 54.9% of SCF defaulters have enough liquid assets to make 1 mortgage payment. The next line shows that 42.5% of defaulters have enough liquid and illiquid assets to make 2 payments, 24.8% of defaulters have enough for 6 payments, and 13.3% of defaulters have enough for one year's worth of payments. The second panel looks at defaulters with negative equity and shows that over $\frac{3}{4}$ of defaulters with negative equity have insufficient liquid assets to make 1 month's payment. A similar pattern emerges in the third panel which looks at defaulters with severe negative equity of -20% or worse.

Table 12 shows that of all defaulters, only 6 percent have negative equity and enough money in their checking and savings account to make 1 mortgage payment. Since the SCF over-samples high-income and wealthy households, if strategic default accounted for a significant fraction of mortgage defaults, we would expect to see evidence of it in these data. We believe that these results, in conjunction with the results in Table 10 may call into question the role of strategic default in the 2007-2009 financial crisis.

6. Conclusion

Previous studies of the empirical determinants of mortgage default have been limited by the fact that loan-level databases have no data on mortgagor employment status and net worth. This study provides to our knowledge the first direct evidence on the impact of employment status, net worth, as well as negative equity on mortgage default by exploiting data from the PSID.

We find that job loss is the main "single trigger" determinant of default in the PSID, and the quantitative importance of job loss is robust to several different specifications of our reduced-form model. Specifically, we find that job loss increases the probability of default between 5 to 13 percentage points. Severe negative equity (-20% or more) also increases the probability of default by 5 to 18 percentage points. The impact of severe negative equity on default drops significantly in magnitude when liquid asset positions are taken into account. Furthermore, we find evidence for the "double trigger" event of job loss and negative equity, as well as job loss and severe negative equity. Specifically, we find that the joint occurrence of both job loss and negative equity raises the unconditional default rate by 11.3% over and above either trigger on its own.

A striking finding of the empirical analysis is on the frequency of strategic default, which is typically defined as default by mortgagors who have sufficient resources to make the mortgage payment. As a suggestive measure, we look at whether or not defaulting households with negative equity have enough liquid assets to make their mortgage payment. We find that strategic default is rare in the PSID. In particular, only 13.9 percent of defaulters in the PSID have sufficient liquid assets to make a mortgage payment. We confirm the rarity of strategic default using data from the SCF which shows that only 6 percent of defaulters have sufficient liquid assets to make one mortgage payment. These findings suggest that strategic default is not a major factor in understanding recent mortgage default decisions, but rather that defaulters may have few options other than to default. These findings have important policy implications. In particular, they suggest that temporary mortgage modifications do not provide a long-term solution to default. Rather, the key to stemming mortgage defaults is developing policies that promote re-employment and higher earnings, such as payroll tax cuts.

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Table 1
Summary Statistics: Demographics, Income, and Wealth

Panel A: Fraction of All Mortgagors and Defaulters (60+ Days Delinquent)

	All	Defaulters		All	Defaulters
Unemployment	7.0%	24.8%	Missing Term Remaining	4.0%	3.7%
Job Loss in Last 6mo.	3.6%	10.1%	Recourse	24.3%	28.4%
Black	21.9%	37.6%	Judicial	39.2%	31.2%
White	71.6%	45.9%	Sand State	15.4%	33.0%
Age	43.7	44.3	HPA (2008-2009)	-7.4%	-11.5%
Male	84.8%	72.5%	Unempl. Rate 2009 (whole %)	9.3	9.8
Married	73.3%	57.8%	Unempl. Growth (2008-2009)	59.5%	61.3%
Recently Divorced	3.1%	5.5%	Hospital Bills/Inc > 10%	1.8%	4.6%
Less than HS Education	9.0%	21.1%	Hospital Bills Outstanding?	32.9%	33.3%
High School Education	27.2%	35.8%	Hospital Bills to Income	2.4%	2.6%
Some College Education	25.7%	18.3%	Pre-1995 Bankruptcy	5.6%	3.7%
College Grad+ Education	32.2%	16.5%	Unsecured Debt ($ thousands)	16.0	27.8
Education Missing	5.9%	8.3%	Auto Debt ($ thousands)	18.1	11.5
Second Mortgage Dummy	19.4%	23.9%	Business Assets ($ thousands)	44.0	1.7
Missing info on Second Mortgage	0.2%	0.9%	IRA ($ thousands)	22.9	0.8
Refinance	47.0%	49.5%	Other Housing ($ thousands)	32.4	2.9
Missing Refinance	0%	0%	Home Value ($ thousands)	243.8	224.7
ARM	9.1%	33.0%	Liquid Assets ($ thousands)	18.2	2.9
Interest Rate on Mortgage (whole %)	5.2	5.7	Stocks ($ thousands)	16.4	4.6
Missing Interest Rate on Mortgage	9.3%	17.9%	Bonds ($ thousands)	13.5	21.3
Term Remaining > 15yrs	68.0%	80.7%	Principal Remaining ($ thousands)	151.8	211.6
30+ Days Delinquent	6.5%	100%	60+ Days Delinquent	3.9%	100%
Observations	2,830	109			

Panel B: Distribution of Wealth Variables of All Mortgagors and Defaulters

Liquid Assets/Income	Mean	≤ 0.05	$0.05 < x \leq 0.10$	$0.10 < x \leq 0.20$	$0.20 < x \leq 0.50$	> 0.50	Missing
All	13.1%	52.1%	16.3%	14.1%	11.8%	5.6%	5.5%
Defaulters	4.1%	84.4%	6.4%	4.9%	3.7%	0.9%	1.8%
Illiquid Assets/Income							
All	61.7%	27.0%	9.2%	15.7%	22.2%	25.9%	17.6%
Defaulters	46.0%	33.0%	11.9%	20.2%	18.3%	16.5%	11.9%

Unsecured Debt/Income	Mean	≤ 0.05	$0.05 < x \leq 0.25$	$0.25 < x \leq 0.50$	$0.50 < x \leq 0.75$	> 0.75	Missing
All	20.8%	51.7%	28.2%	11.3%	3.7%	5.0%	2.5%
Defaulters	96.0%	34.9%	29.4%	12.8%	8.3%	14.7%	1.8%

Debt to Income	Mean	≤ 0.07	$0.07 < x \leq 0.15$	$0.15 < x \leq 0.32$	$0.32 < x \leq 0.40$	> 0.40	Missing
All	18.0%	9.9%	38.3%	42.2%	4.9%	4.7%	2.0%
Defaulters	30.7%	4.6%	12.8%	42.2%	21.1%	19.3%	1.8%

CLTV	Mean	≤ 0.80	$0.80 < x \leq 0.90$	$0.90 < x \leq 1.00$	$1.00 < x \leq 1.20$	> 1.20	Missing
All	65.1%	63.5%	12.5%	11.4%	8.2%	4.4%	8.4%
Defaulters 100.0%	35.8%	12.8%	12.8%	11.0%	27.5%	9.2%	

	Total Income		Income Growth (2007-2009)			
	2007	2009	< -50%	< -10%	$-10\% \leq x < 5\%$	> 5%
All	$99,184	$109,738	3.9%	22.8%	21.2%	56.0%
Defaulters	$74,449	$71,423	13.8%	43.1%	6.4%	50.5%

Table 2
Default Rate by Income and Wealth Status

	CLTV < 100%	CLTV ≥100%	CLTV < 120%	CLTV ≥120%
Unemployed	10.6% (N = 166)	30.0% (N = 30)	12.0% (N = 184)	41.7% (N = 12)
Employed	2.1% (N = 2,308)	10.2% (N = 323)	2.3% (N = 2,520)	22.5% (N = 111)
Liquid Assets < 5%	4.6% (N = 1,242)	15.2% (N = 230)	4.9% (N = 1,397)	30.7% (N = 75)
Liquid Assets ≥ 5%	0.8% (N = 1,232)	5.7% (N = 123)	0.8% (N = 1,307)	14.6% (N = 48)
Illiquid Assets < 5%	3.5% (N = 652)	11.6% (N = 112)	3.8% (N = 731)	24.2% (N = 33)
Illiquid Assets ≥ 5%	2.4% (N = 1,822)	12.0% (N = 241)	2.6% (N = 1,973)	24.4% (N = 90)
Debt-to-Income ≥ 40%	11.1% (N = 99)	30.3% (N = 33)	11.2% (N = 116)	50.0% (N = 16)
Debt-to-Income < 40%	2.4% (N = 2,375)	10.0% (N = 320)	2.6% (N = 2,588)	20.6% (N = 107)
Inc. Growth < -10%	5.1% (N = 553)	21.3% (N = 89)	5.8% (N = 606)	33.3% (N = 36)
Inc. Growth ≥ -10%	2.0% (N = 1,921)	8.7% (N = 264)	2.1% (N = 2,098)	20.7% (N = 87)
Inc. Growth < -50%	12.8% (N = 94)	20.0% (N = 15)	12.6% (N = 103)	33.3% (N = 6)
Inc. Growth ≥ -50%	2.3% (N = 2,380)	11.5% (N = 338)	2.5% (N = 2,601)	23.9% (N = 117)

Table 3
Basic Unemployment and Equity Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

Panel A: Basic Unemployment Results

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.107***	0.137***	0.127***	0.107***	0.136***	0.102***
	(4.29)	(3.56)	(3.38)	(4.29)	(3.63)	(3.37)
Job Loss in Last 6 Months (d)		-0.060	-0.060		-0.015	-0.014
		(-1.21)	(-1.23)		(-1.43)	(-1.28)
Black (d)			0.028***			0.030***
			(2.59)			(2.71)
HS Education (d)			-0.024			-0.013
			(-1.26)			(-1.36)
Some College Education (d)			-0.043**			-0.028***
			(-2.33)			(-3.13)
College Grad+ Education (d)			-0.047***			-0.033***
			(-2.61)			(-3.71)
HPA (2008-2009)			-0.419***			-0.422***
			(-2.84)			(-3.06)
Unemp. Growth (2008-2009)			0.022			0.041
			(0.71)			(1.23)
Other Demographic Controls?	NO	NO	YES	NO	NO	YES
Observations	2,827	2,827	2,820	2,827	2,827	2,820
R^2 / Pseudo R^2	0.020	0.021	0.059	0.039	0.041	0.140

Panel B: Basic Equity Results

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
CLTV	0.132***			0.072***		
	(6.65)			(5.93)		
70% $\leq$ CLTV < 80%		0.002	0.006		0.005	0.004
		(0.27)	(0.58)		(0.28)	(0.24)
80% $\leq$ CLTV < 90%		0.021*	0.023**		0.028**	0.028**
		(1.93)	(2.03)		(2.28)	(2.32)
90% $\leq$ CLTV < 100%		0.025**	0.028**		0.031**	0.033**
		(2.10)	(2.08)		(2.54)	(2.49)
100% $\leq$ CLTV < 120%		0.034**	0.027*		0.038***	0.032**
		(2.25)	(1.73)		(2.92)	(2.40)
CLTV $\geq$ 120%		0.226***	0.203***		0.100***	0.084***
		(5.80)	(5.34)		(8.17)	(7.20)
Black (d)			0.028**			0.029***
			(2.49)			(2.72)
HS Education (d)			-0.032*			-0.020**
			(-1.67)			(-2.08)
Some College Education (d)			-0.050***			-0.034***
			(-2.73)			(-3.88)
College Grad+ Education (d)			-0.052***			-0.038***
			(-2.95)			(-4.47)
HPA (2008-2009)			-0.344**			-0.366***
			(-2.37)			(-2.66)
Unemp. Growth (2008-2009)			0.019			0.033
			(0.62)			(0.95)
Other Demographic Controls?	NO	NO	YES	NO	NO	YES
Observations	2,827	2,827	2,820	2,827	2,827	2,820
R^2 / Pseudo R^2	0.049	0.056	0.083	0.105	0.095	0.173

Notes. Robust t-statistics in parentheses. Asterisk legend: *** pval<0.01, ** pval<0.05, * pval<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Sample size is reduced by 7 observations in column (6) due to missing demographic controls. Variables followed by (d) are indicator variables.

Table 4
Unemployment and Negative Equity Triggers Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.128***	0.126***	0.126***	0.099***	0.091***	0.092***
	(3.45)	(3.37)	(3.39)	(3.12)	(2.95)	(3.10)
Job Loss in Last 6 Months (d)	-0.070	-0.069	-0.072	-0.020**	-0.019*	-0.019*
	(-1.49)	(-1.48)	(-1.53)	(-1.99)	(-1.86)	(-1.87)
CLTV $\geq$ 90%	0.043***			0.035***		
	(3.92)			(4.19)		
CLTV $\geq$ 100%		0.065***			0.036***	
		(4.06)			(4.56)	
CLTV $\geq$ 120%			0.175***			0.058***
			(4.64)			(5.74)
Black (d)	0.024**	0.026**	0.027**	0.024**	0.025**	0.027**
	(2.15)	(2.35)	(2.46)	(2.27)	(2.40)	(2.56)
HS Education (d)	-0.023	-0.024	-0.021	-0.016*	-0.016	-0.014
	(-1.25)	(-1.26)	(-1.16)	(-1.65)	(-1.62)	(-1.50)
Some College Education (d)	-0.039**	-0.037**	-0.036**	-0.026***	-0.025***	-0.025***
	(-2.17)	(-2.06)	(-2.00)	(-2.81)	(-2.73)	(-2.65)
College Grad+ Education (d)	-0.045**	-0.043**	-0.040**	-0.034***	-0.033***	-0.031***
	(-2.53)	(-2.43)	(-2.32)	(-3.79)	(-3.68)	(-3.39)
HPA (2008-2009)	-0.340**	-0.320**	-0.291**	-0.365***	-0.340**	-0.308**
	(-2.39)	(-2.25)	(-2.09)	(-2.67)	(-2.53)	(-2.29)
Unemp. Growth (2008-2009)	0.013	0.016	0.010	0.027	0.033	0.028
	(0.43)	(0.51)	(0.34)	(0.79)	(0.96)	(0.82)
Refinance (d)	0.016**	0.015**	0.015*	0.011	0.011	0.011
	(1.99)	(1.97)	(1.93)	(1.49)	(1.46)	(1.40)
ARM (d)	0.090***	0.091***	0.085***	0.060***	0.063***	0.058***
	(4.30)	(4.40)	(4.07)	(3.66)	(3.84)	(3.51)
Mortgage Term > 15 years (d)	0.015**	0.018**	0.019**	0.013	0.016**	0.018**
	(2.09)	(2.37)	(2.54)	(1.57)	(2.06)	(2.22)
Other Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Other Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.094	0.097	0.118	0.216	0.216	0.233

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 5
Other Triggers Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

Panel A: Moderate Income Loss

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.120***	0.118***	0.119***	0.083***	0.075***	0.077***
	(3.23)	(3.17)	(3.19)	(2.89)	(2.70)	(2.83)
Job Loss in Last 6 Months (d)	-0.063	-0.063	-0.066	-0.017	-0.016	-0.017
	(-1.37)	(-1.36)	(-1.43)	(-1.63)	(-1.43)	(-1.55)
CLTV $\geq$ 90% (d)	0.043***			0.035***		
	(3.91)			(4.24)		
CLTV $\geq$ 100% (d)		0.065***			0.036***	
		(4.05)			(4.63)	
CLTV $\geq$ 120% (d)			0.175***			0.057***
			(4.65)			(5.77)
Recently Divorced (d)	0.003	0.005	0.003	0.009	0.008	0.007
	(0.12)	(0.17)	(0.09)	(0.50)	(0.42)	(0.36)
Hospital Bills/Income > 10% (d)	0.052	0.053	0.059	0.049	0.057	0.068*
	(1.28)	(1.29)	(1.46)	(1.43)	(1.56)	(1.82)
Income Loss < -10% (d)	0.031***	0.030***	0.029***	0.027***	0.026***	0.025***
	(3.00)	(2.93)	(2.85)	(2.93)	(2.84)	(2.70)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.101	0.104	0.125	0.235	0.235	0.251

Panel B: Substantial Income Loss

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.124***	0.122***	0.123***	0.091***	0.083***	0.085***
	(3.33)	(3.25)	(3.27)	(2.84)	(2.66)	(2.77)
Job Loss in Last 6 Months (d)	-0.067	-0.067	-0.069	-0.019*	-0.018*	-0.019*
	(-1.45)	(-1.44)	(-1.50)	(-1.90)	(-1.71)	(-1.84)
CLTV $\geq$ 90% (d)	0.042***			0.033***		
	(3.84)			(3.99)		
CLTV $\geq$ 100% (d)		0.064***			0.035***	
		(3.99)			(4.39)	
CLTV $\geq$ 120% (d)			0.175***			0.057***
			(4.63)			(5.54)
Recently Divorced (d)	-0.006	-0.005	-0.007	0.003	0.003	0.001
	(-0.20)	(-0.16)	(-0.23)	(0.19)	(0.16)	(0.06)
Hospital Bills/Income > 10% (d)	0.051	0.052	0.059	0.055*	0.063*	0.071**
	(1.33)	(1.33)	(1.50)	(1.67)	(1.78)	(1.97)
Income Loss < -50% (d)	0.093***	0.092***	0.091***	0.076***	0.076**	0.074**
	(2.95)	(2.91)	(2.88)	(2.59)	(2.57)	(2.46)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.105	0.108	0.129	0.238	0.238	0.255

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 6
Wealth Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.118***	0.117***	0.117***	0.085***	0.078***	0.078***
	(3.22)	(3.17)	(3.18)	(3.23)	(3.04)	(3.14)
Job Loss in Last 6 Months (d)	-0.065	-0.065	-0.068	-0.017*	-0.017*	-0.018*
	(-1.41)	(-1.41)	(-1.49)	(-1.75)	(-1.65)	(-1.83)
CLTV $\geq$ 90% (d)	0.035***			0.026***		
	(3.16)			(3.05)		
CLTV $\geq$ 100% (d)		0.058***			0.030***	
		(3.56)			(3.77)	
CLTV $\geq$ 120% (d)			0.174***			0.057***
			(4.63)			(5.55)
Recently Divorced (d)	-0.006	-0.005	-0.007	0.001	0.000	-0.000
	(-0.21)	(-0.18)	(-0.24)	(0.04)	(0.02)	(-0.03)
Hospital Bills/Income > 10% (d)	0.043	0.044	0.049	0.037	0.044	0.048
	(1.09)	(1.10)	(1.23)	(1.24)	(1.40)	(1.49)
Income Loss < -50% (d)	0.093***	0.092***	0.090***	0.083***	0.084***	0.077**
	(3.02)	(2.99)	(2.93)	(2.62)	(2.70)	(2.50)
0.05 < Liquid Assets/Inc < 0.10 (d)	-0.027***	-0.028***	-0.028***	-0.026***	-0.026***	-0.026***
	(-3.24)	(-3.27)	(-3.31)	(-3.34)	(-3.53)	(-3.38)
0.10 < Liquid Assets/Inc < 0.20 (d)	-0.023***	-0.024***	-0.027***	-0.023***	-0.024***	-0.027***
	(-2.69)	(-2.76)	(-3.20)	(-2.79)	(-3.05)	(-3.73)
0.20 < Liquid Assets/Inc < 0.50 (d)	-0.025***	-0.026***	-0.027***	-0.023***	-0.024***	-0.026***
	(-2.85)	(-2.96)	(-3.18)	(-2.59)	(-2.67)	(-3.15)
Liquid Assets/Inc > 0.50 (d)	-0.035***	-0.035***	-0.035***	-0.035***	-0.036***	-0.035***
	(-3.40)	(-3.40)	(-3.37)	(-4.40)	(-4.60)	(-3.56)
0.05 < Illiquid Assets/Inc < 0.10 (d)	-0.017	-0.014	-0.020	-0.003	-0.002	-0.006
	(-0.79)	(-0.68)	(-0.94)	(-0.27)	(-0.18)	(-0.50)
0.10 < Illiquid Assets/Inc < 0.20 (d)	-0.019	-0.017	-0.018	-0.006	-0.005	-0.004
	(-0.99)	(-0.89)	(-0.91)	(-0.61)	(-0.53)	(-0.42)
0.20 < Illiquid Assets/Inc < 0.50 (d)	-0.030*	-0.029	-0.033*	-0.016*	-0.015	-0.017*
	(-1.67)	(-1.59)	(-1.81)	(-1.81)	(-1.63)	(-1.92)
Illiquid Assets/Inc > 0.50 (d)	-0.026	-0.025	-0.028	-0.020**	-0.019**	-0.020**
	(-1.47)	(-1.38)	(-1.59)	(-2.25)	(-2.13)	(-2.26)
0.05 < Unsecured Debt/Inc < 0.10 (d)	0.008	0.008	0.009	0.012	0.012	0.015
	(1.02)	(1.01)	(1.12)	(1.29)	(1.27)	(1.55)
0.10 < Unsecured Debt/Inc < 0.20 (d)	0.009	0.011	0.014	0.020	0.022	0.026
	(0.72)	(0.89)	(1.16)	(1.29)	(1.38)	(1.58)
0.20 < Unsecured Debt/Inc < 0.50 (d)	0.030	0.030	0.030	0.029	0.032	0.035
	(1.12)	(1.14)	(1.18)	(1.30)	(1.43)	(1.57)
Unsecured Debt/Inc > 0.50 (d)	0.045*	0.043*	0.051**	0.033*	0.032*	0.041**
	(1.87)	(1.78)	(2.15)	(1.80)	(1.71)	(2.03)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.117	0.120	0.143	0.284	0.287	0.310

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 7
Summary Statistics: Pre-1996 Bankruptcies and Defaults, PSID

Panel A: Pre-1996 Bankruptcies

	Observations	Fraction (%)	Avg. Age
No Bankruptcy History	2,859	94.14	44.26
Pre-1996 Bankruptcies	178	5.86	45.48

Panel B: Default Fractions

	Observations	60-Day Delinquency (%)	30-Day Delinquency (%)
No Bankruptcy History	2,859	3.85	6.44
Pre-1996 Bankruptcies	178	2.81	6.18

Table 8
Pre-1996 Bankruptcy and Mortgage Default Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date.

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.123***	0.121***	0.122***	0.089***	0.082***	0.084***
	(3.31)	(3.24)	(3.26)	(2.81)	(2.63)	(2.74)
Job Loss in Last 6 Months (d)	-0.066	-0.066	-0.069	-0.018*	-0.017	-0.018*
	(-1.43)	(-1.42)	(-1.49)	(-1.79)	(-1.62)	(-1.74)
CLTV $\geq$ 90% (d)	0.043***			0.034***		
	(3.90)			(4.04)		
CLTV $\geq$ 100% (d)		0.064***			0.035***	
		(4.00)			(4.38)	
CLTV $\geq$ 120% (d)			0.175***			0.057***
			(4.62)			(5.55)
Recently Divorced (d)	-0.005	-0.004	-0.007	0.003	0.003	0.001
	(-0.19)	(-0.15)	(-0.23)	(0.18)	(0.15)	(0.06)
Hospital Bills/Income > 10% (d)	0.052	0.053	0.059	0.057*	0.065*	0.074**
	(1.35)	(1.35)	(1.51)	(1.69)	(1.79)	(2.00)
Income Loss < -10% (d)	0.094***	0.093***	0.091***	0.077***	0.077**	0.075**
	(2.97)	(2.93)	(2.90)	(2.58)	(2.56)	(2.46)
Pre-1995 Bankruptcy (d)	-0.024*	-0.021	-0.016	-0.017	-0.015	-0.014
	(-1.88)	(-1.65)	(-1.25)	(-1.56)	(-1.30)	(-1.13)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.105	0.109	0.129	0.239	0.240	0.256

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 9
Double Trigger Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date.

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.057**	0.073***	0.082***	0.064***	0.060***	0.061***
	(2.45)	(3.05)	(3.50)	(3.22)	(3.04)	(3.12)
CLTV $\geq$ 90%	0.032***			0.037***		
	(2.95)			(3.50)		
CLTV $\geq$ 100%		0.056***			0.045***	
		(3.41)			(3.52)	
CLTV $\geq$ 120%			0.167***			0.104***
			(4.24)			(3.66)
Unemployed*CLTV $\geq$ 90% (d)	0.143**			.079		
	(2.06)			(1.50)		
Unemployed*CLTV $\geq$ 100% (d)		0.093			.009	
		(1.13)			(0.17)	
Unemployed*CLTV $\geq$ 120% (d)			0.075			-.014
			(0.54)			(-0.19)
Hospital Bills/Income > 10% (d)	0.049	0.051	0.058	0.052	0.059*	0.065*
	(1.30)	(1.30)	(1.48)	(1.64)	(1.73)	(1.87)
Income Loss < -50%	0.095***	0.095***	0.092***	0.078***	0.077***	0.077***
	(3.03)	(2.99)	(2.92)	(2.67)	(2.64)	(2.62)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2	0.109	0.108	0.127	0.256	0.256	0.256

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 10
Evidence on Strategic Default: PSID

Panel A: All Defaulters

	Obs.	Mean	1	5	10	25	50	75	90	95	99
						Percentile of Distribution					
Liq Assets ($ thousands)	112	2.8	0	0	0	0	0	2	5	10	35
Stocks ($ thousands)	112	4.4	0	0	0	0	0	0	0	0.05	200
Bonds ($ thousands)	115	20.3	0	0	0	0	0	0	0	50	550
Retirement ($ thousands)	115	0.8	0	0	0	0	0	0	0	4	16
Unsecured Debt ($ thousands)	113	26.6	0	0	0	0.5	10	30	50	100	300
Liq Assets / Monthly Payment	110	1.4	0	0	0	0	0.3	1.1	4.5	5.4	15.9
Illquid Assets / Monthly Payment	113	9.7	0	0	0	0	0	0	3.8	49.4	261.2
LA / Payment > 1 *or* ILA / Payment > 1						41 (35.7%)					
LA / Payment > 2 *or* ILA / Payment > 2						31 (27.0%)					
LA / Payment > 6 *or* ILA / Payment > 6						17 (14.8%)					
LA / Payment > 12 *or* ILA / Payment > 12						14 (12.2%)					

Panel B: Negative Equity (CLTV > 100%) Defaulters

	Obs.	Mean	1	5	10	25	50	75	90	95	99
						Percentile of Distribution					
Liq Assets ($ thousands)	44	2.8	0	0	0	0	0.7	2	10	12	35
Stocks ($ thousands)	44	7.0	0	0	0	0	0	0	0	2	300
Bonds ($ thousands)	44	26.4	0	0	0	0	0	0	0	50	800
Retirement ($ thousands)	44	0.5	0	0	0	0	0	0	0	0	14
Unsecured Debt ($ thousands)	43	34.7	0	0	0	1	10	30	46	100	500
Liq Assets / Monthly Payment	44	1.3	0	0	0	0	0.4	1.1	4.5	4.7	15.9
Illquid Assets / Monthly Payment	44	9.8	0	0	0	0	0	0.0	12.8	22.7	262.3
LA / Payment > 1 *or* ILA / Payment > 1						16 (36.4%)					
LA / Payment > 2 *or* ILA / Payment > 2						12 (27.3%)					
LA / Payment > 6 *or* ILA / Payment > 6						6 (13.6%)					
LA / Payment > 12 *or* ILA / Payment > 12						5 (11.4%)					

Panel C: Severe Negative Equity (CLTV > 120%) Defaulters

	Obs.	Mean	1	5	10	25	50	75	90	95	99
						Percentile of Distribution					
Liq Assets ($ thousands)	31	3.6	0	0	0	0	0.8	3	10	15	35
Stocks ($ thousands)	31	9.7	0	0	0	0	0	0	0	0	300
Bonds ($ thousands)	31	37.1	0	0	0	0	0	0	0	300	800
Retirement ($ thousands)	31	0.6	0	0	0	0	0	0	0	6	14
Unsecured Debt ($ thousands)	30	37.8	0	0	0	0	4.2	20	68	300	500
Liq Assets / Monthly Payment	31	1.7	0	0	0	0	0.4	1.9	4.6	6.5	15.9
Illquid Assets / Monthly Payment	31	13.5	0	0	0	0	0	0	14.7	115.4	262.3
LA / Payment > 1 *or* ILA / Payment > 1						12 (38.7%)					
LA / Payment > 2 *or* ILA / Payment > 2						11 (35.5%)					
LA / Payment > 6 *or* ILA / Payment > 6						5 (16.1%)					
LA / Payment > 12 *or* ILA / Payment > 12						4 (12.9%)					

Notes. For more observations, this table includes all non-disabled working age (24 to 65) heads of households in the PSID with no restrictions on loan to values or labor force participation. Liquid assets include checking or savings accounts, money market funds, certificates of deposit, government savings bonds, or Treasury bills. Payment includes both first and second mortgage payments. Illiquid assets include stocks, retirement savings, and bonds.

Table 11
Measures of Strategic Default, SCF

Panel A: All Defaulters

			Percentile of Distribution								
	Obs.	**Mean**	**1**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**99**
Liquid Assets ($ thousands)	113	6.02	0	0	0.01	0.15	0.6	2	6.98	15.1	116.9
Stocks ($ thousands)	113	0.91	0	0	0	0	0	0	0.57	1.6	27
Bonds ($ thousands)	113	0.02	0	0	0	0	0	0	0	0	1
IRA ($ thousands)	113	8.80	0	0	0	0	0	0	12	30	150
Unsecured Balance ($ thousands)	113	13.23	0	0	0	0	0.52	9	40	80	175
Liquid Assets/ Monthly Payment	113	2.36	0	0	0.01	0.12	0.57	1.39	4.29	5.89	39.58
Illiquid Assets/ Monthly Payment	113	8.90	-27.78	-11.11	0	0	0	5.63	14.58	50.00	128.93
	1356	-692.54	0	0.32	0.88	2.98	9.70	34.03	117.59	205.07	666.25
LA / Payment > 1 or ILA / Payment > 1						62 (54.9%)					
LA / Payment > 2 or ILA / Payment > 2						48 (42.5%)					
LA / Payment > 6 or ILA / Payment > 6						28 (24.8%)					
LA / Payment > 12 or ILA / Payment > 12						15 (13.3%)					

Panel B: All Defaulters with Negative Equity (CLTV>100%)

			Percentile of Distribution								
	Obs.	**Mean**	**1**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**99**
Liquid Assets ($ thousands)	39	5.71	0	0	0	0.1	0.44	1.5	6.98	11.4	173
Stocks ($ thousands)	39	0.09	0	0	0	0	0	0	0.57	0.75	1.1
Bonds ($ thousands)	39	0.04	0	0	0	0	0	0	0	0	1.6
IRA ($ thousands)	39	2.31	0	0	0	0	0	0	12	20	30
Unsecured Balance ($ thousands)	39	9.47	0	0	0	0	0.3	9	32	50	100
Liquid Assets/ Monthly Payment	39	0.84	0	0	0	0.07	0.30	0.61	3.49	4.75	8.83
Illiquid Assets/ Monthly Payment	39	4.67	-27.78	-11.11	0	0	0	3.23	8.06	62.56	106.43
LA / Payment > 1 or ILA / Payment > 1						17 (43.6%)					
LA / Payment > 2 or ILA / Payment > 2						13 (33.3%)					
LA / Payment > 6 or ILA / Payment > 6						5 (12.8%)					
LA / Payment > 12 or ILA / Payment > 12						2 (5.1%)					

Panel C: All Defaulters with Severe Negative Equity (CLTV>120%)

			Percentile of Distribution								
	Obs.	**Mean**	**1**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**99**
Liquid Assets ($ thousands)	18	1.37	0	0	0	0.06	0.54	1.50	6.98	9	9
Stocks ($ thousands)	18	0.00	0	0	0	0	0	0	0	0.05	0.05
Bonds ($ thousands)	18	0.09	0	0	0	0	0	0	0	1.6	1.6
IRA ($ thousands)	18	1.00	0	0	0	0	0	0	6	12	12
Unsecured Balance ($ thousands)	18	10.93	0	0	0	0	0.41	6	50	100	100
Liquid Assets/ Monthly Payment	18	0.68	0	0	0	0.03	0.28	0.55	3.49	3.75	3.75
Illiquid Assets/ Monthly Payment	18	-0.25	-27.78	-27.78	0	0	0	1.45	6.07	8.06	8.06
LA / Payment > 1 or ILA / Payment > 1						7 (38.9%)					
LA / Payment > 2 or ILA / Payment > 2						5 (27.8%)					
LA / Payment > 6 or ILA / Payment > 6						2 (11.1%)					
LA / Payment > 12 or ILA / Payment > 12						0 (00.0%)					

Notes. SCF Restricted sample (See above). Illiquid assets include stocks, bonds, and retirement savings. Liquid assets include checking, savings, and CDs. Monthly payment includes both first and second mortgage payments.

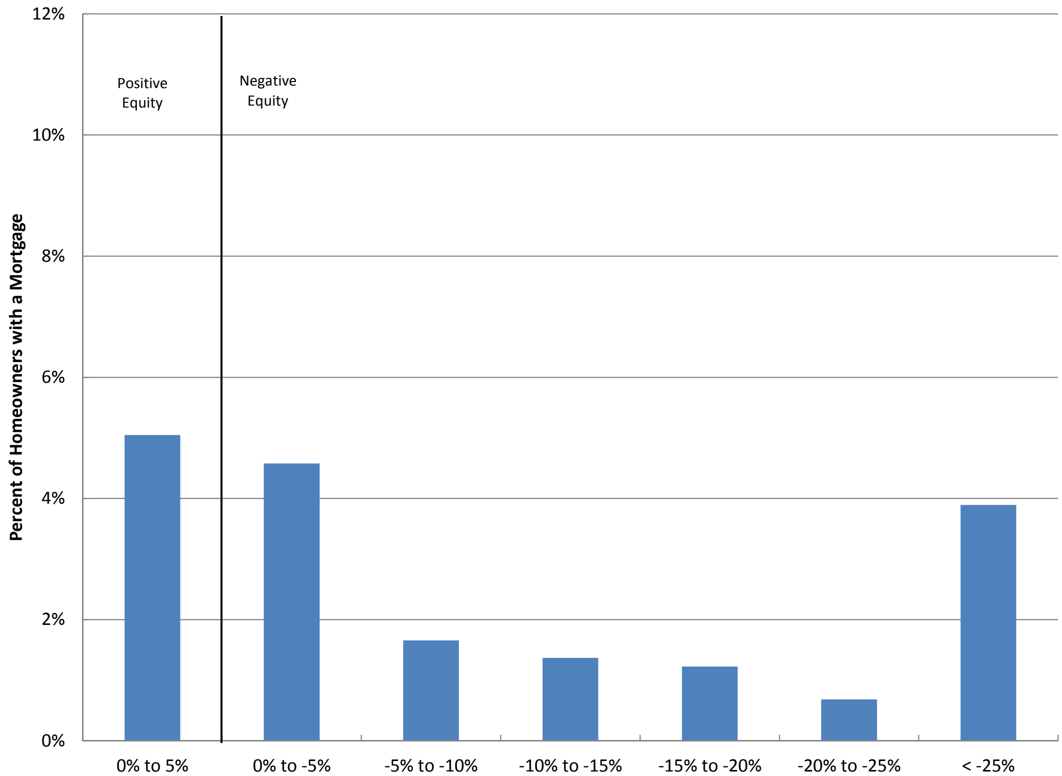
Table 12
Additional Measures of Strategic Default Among Mortgagors who were 2mo+ Delinquent over Last 12 Months, SCF

Among Defaulters over Prior 12 mo.		
	Fraction	Observations
Fraction of Defaulters with Insufficient Checking and Savings to Cover 1 Mo. Mortgage Payment and Credit Constrained	0.23	113
Fraction of Defaulters who have Sufficient Checking and Savings to Cover 1 Mo. Mortgage Payment and who have $CLTV > .9$	0.097	113
Fraction of Defaulters who have Sufficient Checking and Savings to Cover 1 Mo. Mortgage Payment and who have $CLTV > 1$	0.061	113

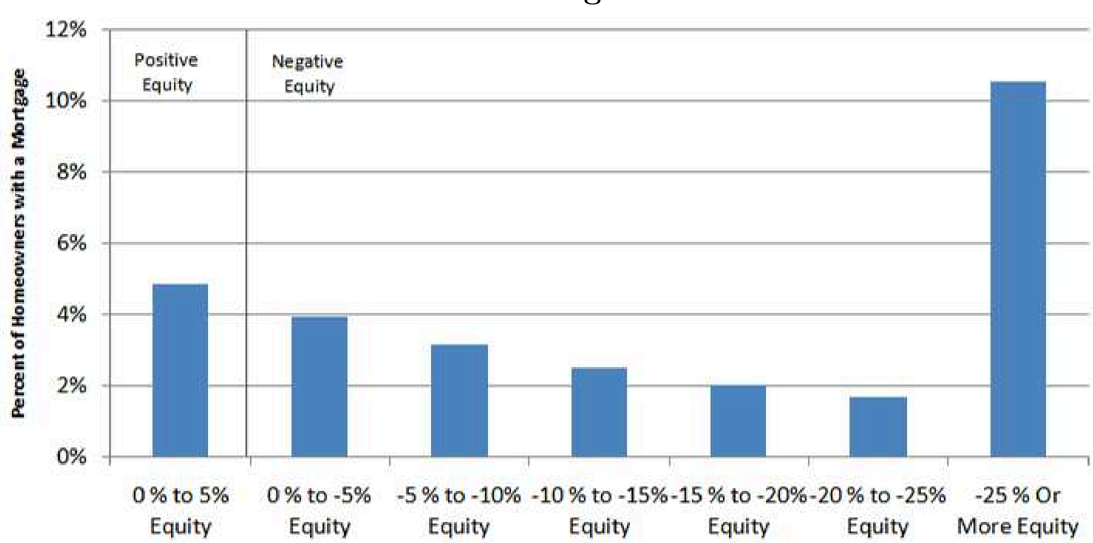
Notes. SCF Restricted sample (See above). Liquid assets include checking and savings only. Credit denial refers to denial between 2007 and 2009. Monthly payment includes both first and second mortgage payments.

Figure 1. Equity Distribution

PSID

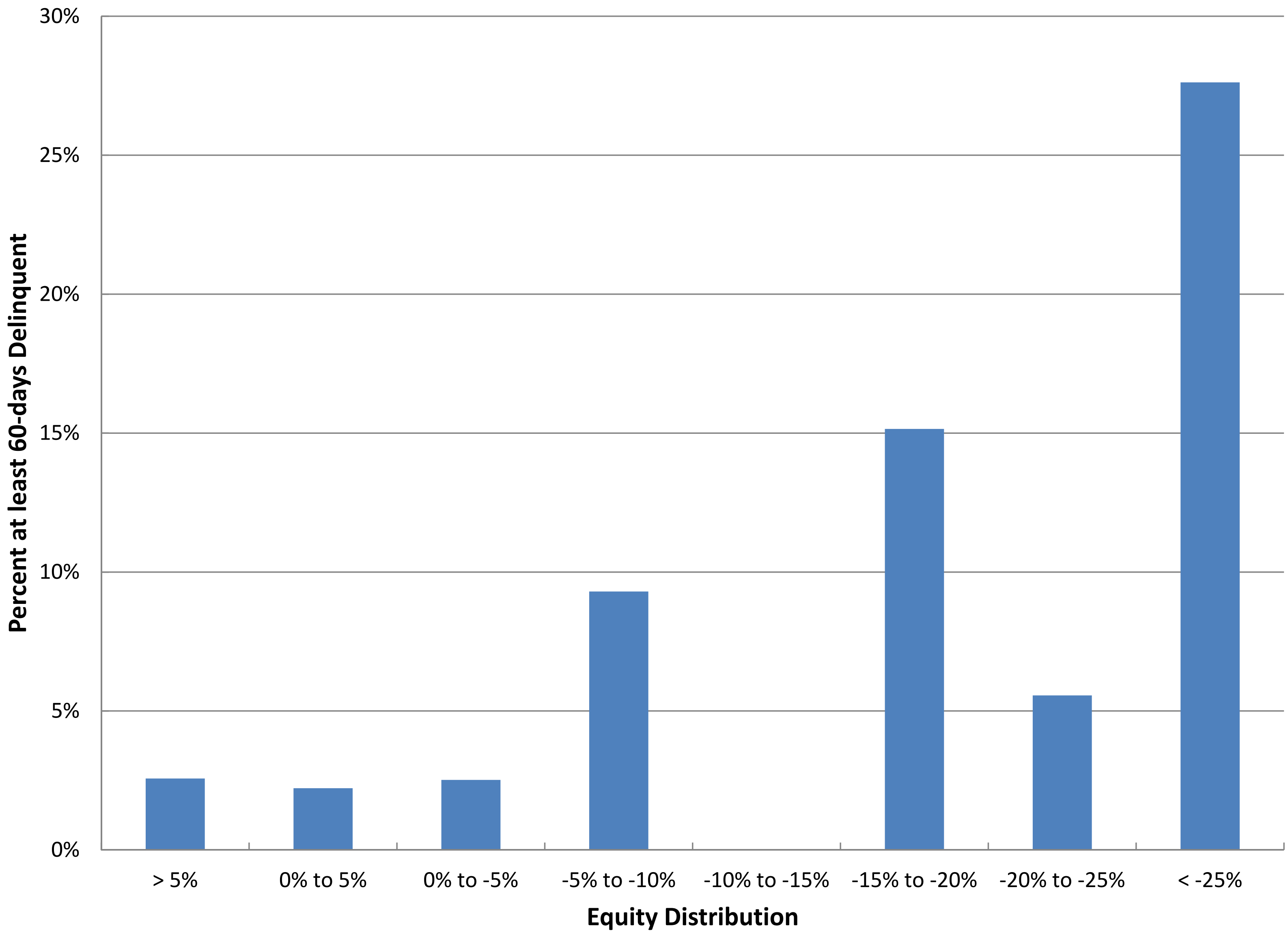


Corelogic



Notes: PSID Mortgagors. CoreLogic Images Replicated from 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`

Figure 2. Default Rates and Negative Equity



Notes: PSID Mortgagors.

A. Data Details

A.1. PSID Interview Questions

The home value is self-reported: "A20. Could you tell me what the present value of your (house/apartment) is–I mean about how much would it bring if you sold it today?" The remaining principal is also self-reported: "A24. About how much is the remaining principal on this mortgage?" The mortgage default information is measured as of the survey date and also self-reported: "A27FOR2. How many months are you behind?"

A.2. SCF Interview Questions

The survey asks various questions regarding credit constraints, default, and house prices. They ask directly about credit constraints: "In the past [two] years, has a particular lender or creditor turned down any request you or your (husband/wife/partner) made for credit, or not given you as much credit as you applied for?" The question regarding default is about all loans: "Now thinking of all the various loan or mortgage payments you made during the last year, were all the payments made the way they were scheduled, or were payments on any of the loans sometimes made later or missed?" There is a follow up default question that asks whether or not the respondent was ever two or more months late. The house value is self-reported and so is the remaining principal, similar to the PSID.

A.3. Discussion of Weights

We do not weight the observations due to the fact that default outcomes are not post-stratum in the PSID. The point is best made with an important example. The Office of Thrift Supervision (OTS) publishes a mortgage delinquency report every quarter based on nationally representative data. They report that in 2009-Q3, roughly 6.2% of mortgages were delinquent. In the 2009 PSID, the unweighted default rate among mortgagors is 3.86%. However, the default rate in the 2009 PSID, weighted using the family weights, is only 3.15%. 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 SCF.

Table 13
PSID Sample Comparison: Unrestricted vs. Restricted vs. External Data

	PSID				Population	
Variable	Full Sample		Restricted Sample			
	Mean	N	Mean	N	Mean	Source
30+ Days Late (d)	0.064	3349	0.062	2814	0.114	2009-Q4 Mortgage Metrics Report
60+ Days Late (d)	0.039	3349	0.035	2814	0.052	2009-Q4 Mortgage Metrics Report
90+ Days Late (d)	0.023	3349	0.019	2814	0.032	2009-Q4 Mortgage Metrics Report
Unemployment (d)	0.060	3342	0.070	2814	0.093	BLS All 16+
90% $<$ CLTV $\leq$ 100% (d)	0.127	3349	0.138	2814	See Chart	CoreLogic
100% $<$ CLTV $\leq$ 110% (d)	0.034	3349	0.035	2814	See Chart	CoreLogic
110% $<$ CLTV $\leq$ 120% (d)	0.023	3349	0.025	2814	See Chart	CoreLogic
CLTV $>$ 120% (d)	0.042	3349	0.038	2814	See Chart	CoreLogic
60+ Days Late if 90% $<$ CLTV $\leq$ 100% (d)	0.047	426	0.039	387		
60+ Days Late if 100% $<$ CLTV $\leq$ 110% (d)	0.070	114	0.061	99		
60+ Days Late if 110% $<$ CLTV $\leq$ 120% (d)	0.066	76	0.072	69		
60+ Days Late if CLTV $>$ 120% (d)	0.252	139	0.178	107		
60+ Days Late if Unemployed and 90% $<$ CLTV $\leq$ 100% (d)	0.263	19	0.278	18		
60+ Days Late if Unemployed and 100% $<$ CLTV $\leq$ 110% (d)	0.250	8	0.250	8		
60+ Days Late if Unemployed and 110% $<$ CLTV $\leq$ 120% (d)	0.143	7	0.143	7		
60+ Days Late if Unemployed and CLTV $>$ 120% (d)	0.417	12	0.333	9		
60+ Days Late if Employed and 90% $<$ CLTV $\leq$ 100% (d)	0.037	407	0.027	369		
60+ Days Late if Employed and 100% $<$ CLTV $\leq$ 110% (d)	0.057	106	0.044	91		
60+ Days Late if Employed and 110% $<$ CLTV $\leq$ 120% (d)	0.058	69	0.065	62		
60+ Days Late if Employed and CLTV $>$ 120% (d)	0.238	126	0.163	98		

B. Robustness Checks

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, (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 is no data on consecutive unemployment spells, and lastly, and (iv) since the default status at the survey date is unknown and since they record negative equity, wealth, and employment as of the survey date, causal inference is nearly impossible.[42] 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 is also considerably smaller, but the SCF specifically samples high-net-worth individuals which is useful in the discussion of strategic default. For the purposes of comparability, we restrict the sample to working age heads of households (24yrs to 65yrs) who are labor force participants and have a mortgage in 2009.

B.1.1. SCF Summary

Table 14 summarizes the SCF variables of interest. While there are only 1,482 observations, we have 113 default observations, where default is defined to be 60+ days late over the prior 12 months on any debt, which is roughly the same number of default observations as the PSID (however the PSID measure of default is different). Similar to the PSID, in the SCF 88% of the heads are male and the average age is 46 which is comparable to the sample in Table 1. Mean income is significantly higher (roughly $30,000 higher) in the SCF sample compared to the PSID sample.

In terms of financial health, 8% of the entire sample has a combined loan to value ratio over 100%, and 3% of the entire sample has a combined loan to value ratio over 120%. Almost 49% of SCF mortgagors have a ratio of liquid assets (which includes savings, checking, and CDs) to annual gross income of less than 5%. Moreover, 12% of the sample has a ratio of unsecured debt balances (which includes credit card, retail card, and other unsecured

[42] See Herkenhoff [2013] for an IV correction to this problem based on the panel aspect of the dataset.

balances) to annual gross income of over 75%. Only 3% of mortgagors have gone over their credit limit, i.e. they have a credit utilization rate greater than 100%.

B.2. SCF Defaulter Characterization

Turning to the defaulter versus average mortgagor comparison, the SCF exhibits the same unemployment pattern as the PSID: only 6% of the entire mortgage sample is unemployed, whereas 17% of defaulters are unemployed. Likewise, 3% of the entire mortgage sample has severe negative equity of -20% or worse while over 16% of defaulters have severe negative equity of -20% or worse. Of importance is the fact that defaulters in the SCF have *significantly* lower incomes than the average SCF mortgagor, roughly $78,000 lower.

There is also an interesting correlation between credit denial and default; roughly 40% of defaulters were denied credit between 2007 and 2009 versus 16% for the entire mortgagor sample. The typical story is that defaulters have low credit scores, and thus are denied credit more often. A more interesting question is whether or not credit denial leads to default.[43]

B.3. Unemployment and Default in the SCF

Table 15 reports both linear probability (LPM) and logit results for a regression of the SCF default indicator on unemployment as of the survey date. Columns (1)-(3) are identical linear probability models except for the varying negative equity cutoffs. For comparability with the PSID, column (1) uses a combined loan to value (CLTV) cutoff of 90%, column (2) uses a CLTV>100% cutoff, and column (3) uses a CLTV>120% cutoff. Likewise, columns (4)-(6) are logit models with the same set of negative equity cutoffs. The controls included each regression include balance sheet controls for liquid assets, illiquid assets, and unsecured debt; demographic controls for age, rage, sex, marital status, and education; and mortgage controls for the presence of a second mortgage, whether there is 15 or more years remaining on the term of the loan, a prior refinancing, and whether the mortgage is an ARM.

Unemployment in every specification is a strongly correlated default (however, the interpretation here is far from causal), as in the PSID study. We interpret the linear probability model results in column (3) as follows: an unemployed person is 12.7% more likely to have defaulted on any of their debts over the prior 12 months than an employed person, and a mortgagor with severe negative equity of -20% or worse is 23.1% more likely to have defaulted on any of their debts over the prior 12 months than a mortgagor with a better equity position. To discipline the model's fit, we include an identical logit specification in column (6). The logit results reveal that an unemployed mortgagor is 9.9% more likely to have defaulted their debts over the prior 12 months relative to an employed mortgagor. A mortgagor with

[43] See Herkenhoff [2013] for more on this topic.

severe negative equity of -20% or worse is 13.1% more likely to have defaulted their debts over the prior 12 months than a mortgagor with a better equity position. The logit model in column (6) corrects for the well known deficiencies of the linear probability model and is thus our preferred specification.

As in the PSID, medical payments (proxied by other loan payments which includes medical loan payments) is not a strong predictor of default, and neither is recent divorce (the recent divorce point estimate is large, but not significantly different from zero). We do not include credit card utilization rates or credit denial status due to the inherent endogeneity induced by the survey timing.

B.4. Trigger Analysis: Unemployment and Negative Equity in the SCF

Table 16 provides more mixed evidence for the double trigger event of unemployment and negative equity. In every column , the point estimates for the coefficients on unemployment *alone* and negative equity *alone* are of the same magnitude as Table 15 (based on the PSID), suggesting a limited role for interactions between unemployment and negative equity. For example, in column (6), an unemployed mortgagor is 9.8% more likely to have defaulted their debts over the prior 12 months relative to an employed mortgagor (versus 9.9% in Table 15). Similarly, a mortgagor with severe negative equity of -20% or worse is 13.1% more likely to have defaulted their debts over the prior 12 months than a mortgagor with a better equity position, the exact same point estimate as in Table 15. The lack of an interaction effect is likely due to the fact that there are only 18 default observations in the SCF with severe negative equity of -20% or worse. With such limited variation, it becomes nearly impossible to obtain precise point estimates. We do note however, that the point estimates for the interaction term between unemployment and severe negative equity is large even though is is not statistically different from zero.

Table 14
Summary Statistics and Defaulter Comparison: SCF

	Means	
Demographics	All Mortgagors	Defaulters
Unemployed at Survey Date, 2009 (d)	0.06	0.17
Male Indicator (d)	0.88	0.81
Married (d)	0.76	0.69
Age	46.11	43.70
Black (d)	0.06	0.12
College Educated (d)	0.59	0.34
Recently Divorced 2007-2009 (d)	0.03	0.05

	Means	
Income	All Mortgagors	Defaulters
Total Income 2007	137,231	59,265
Total Income 2009	156,307	58,458
5% $\leq$ Income Loss < -10% from 2007 to 2009 (d)	0.04	0.02
Income Loss < -10% from 2007 to 2009 (d)	0.25	0.36
Income Loss < -50% from 2007 to 2009 (d)	0.09	0.12

	Means	
Mortgage	All Mortgagors	Defaulters
60 + Days Late on Any Debt over Prior 12 Months (d)	0.08	1.00
CLTV < .7 (d)	0.60	0.32
.7 $\leq$ CLTV < .8 (d)	0.08	0.08
.8 $\leq$ CLTV < .9 (d)	0.08	0.13
.9 $\leq$ CLTV < 1 (d)	0.06	0.11
1 $\leq$ CLTV < 1.2 (d)	0.05	0.13
1.2 $\leq$ CLTV (d)	0.03	0.16
Loan Term > 15 years (d)	0.06	0.08
Refinanced (d)	0.17	0.13
Variable Rate Mortgage (d)	0.15	0.22
Second Mortgage Presence (d)	0.08	0.12

	Means	
Financial	All Mortgagors	Defaulters
Liquid Assets to Income < 5% (d)	0.49	0.82
Illiquid Assets to Income < 5% (d)	0.14	0.33
25% < Unsecured DTI $\leq$ 50% (d)	0.04	0.04
50% < Unsecured DTI $\leq$ 75% (d)	0.01	0.03
75% < Unsecured DTI (d)	0.12	0.19
Other Loan Payments (Including Medical) to Income > 1% (d)	0.01	0.01
Other Loan Payments (Including Medical) to Income	0.10	0.11
Difference in Other Loan Payments (Including Medical) from 2007 to 2009	320	47
.8 $\leq$ Credit Utilization Rate < .9 (d)	0.03	0.10
.9 $\leq$ Credit Utilization Rate < 1 (d)	0.01	0.04
1 $\leq$ Credit Utilization Rate (d)	0.03	0.16
Denied Credit Between 2007 and 2009 (d)	0.16	0.40
Discouraged Borrower Between 2007 and 2009 (d)	0.12	0.42
Observations	1482	113

Notes. SCF Restricted Sample.

Table 15
Single Trigger Results, Dependent Variable is 60+ Days Late Indicator on All Debts over Prior 12 Months to 2009 Survey Date, SCF

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed at Survey Date, 2009 (d)	0.127***	0.126***	0.127***	0.101***	0.099***	0.099***
	(3.06)	(3.04)	(3.11)	(3.12)	(3.15)	(3.17)
CLTV > .9 (d)	0.110***			0.073***		
	(3.93)			(3.32)		
CLTV > 1 (d)		-0.005			-0.002	
		(-0.15)			(-0.07)	
CLTV > 1.2 (d)			0.231***			0.131**
			(3.25)			(2.48)
Recently Divorced 2007-2009 (d)	0.046	0.048	0.057	0.032	0.039	0.048
	(0.87)	(0.90)	(1.07)	(0.70)	(0.78)	(0.98)
Other Loan Payments (Including Medical) to Income > 1% (d)	-0.055	-0.046	-0.056	-0.046	-0.043	-0.047*
	(-0.76)	(-0.61)	(-0.93)	(-1.42)	(-1.25)	(-1.80)
Income Loss < -50% from 2007 to 2009 (d)	0.008	0.008	0.006	0.006	0.004	0.002
	(0.31)	(0.31)	(0.23)	(0.28)	(0.19)	(0.08)
Balance Sheet Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,482	1,482	1,482	1,482	1,482	1,482
R-squared / Pseudo R-Squared	0.122	0.105	0.125	0.212	0.194	0.209

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. SCF Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, and mortgage term greater than 15 years dummy. Balance sheet controls include low liquid assets, low illiquid assets, and unsecured debt dummies. Coefficients reported in columns (1)-(3). Average marginal effects reported in columns (4)-(6).

Table 16

Double Trigger Results, Dependent Variable is 60+ Days Late Indicator on All Debts over Prior 12 Months to 2009 Survey Date, SCF

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed at Survey Date, 2009 (d)	0.116***	0.089**	0.115***	0.101***	0.098***	0.098***
	(2.69)	(2.06)	(2.78)	(3.16)	(3.11)	(3.15)
CLTV > .9 (d)	0.106***			0.072***		
	(3.71)			(3.29)		
CLTV > 1 (d)		-0.016			-0.002	
		(-0.46)			(-0.08)	
CLTV > 1.2 (d)			0.208***			0.131**
			(2.83)			(2.49)
Unemployed*CLTV>.9 (d)	0.069			-.019		
	(0.51)			(-.203)		
Unemployed*CLTV>1 (d)		0.182			.032	
		(1.54)			(.434)	
Unemployed*CLTV>1.2 (d)			0.278			.155
			(1.28)			(.82)
Recently Divorced 2007-2009 (d)	0.045	0.045	0.055	0.034	0.038	0.048
	(0.84)	(0.83)	(1.04)	(0.73)	(0.78)	(0.98)
Other Loan Payments (Including Medical) to Income > 1% (d)	-0.055	-0.044	-0.055	-0.047	-0.043	-0.046*
	(-0.75)	(-0.58)	(-0.89)	(-1.45)	(-1.24)	(-1.78)
Income Loss < -50% from 2007 to 2009 (d)	0.009	0.010	0.007	0.005	0.005	0.002
	(0.35)	(0.40)	(0.28)	(0.21)	(0.21)	(0.09)
Balance Sheet Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,482	1,482	1,482	1,482	1,482	1,482
R-squared /Pseudo R2	0.123	0.109	0.127	0.213	0.194	0.209

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. SCF Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, and mortgage term greater than 15 years dummy. Balance sheet controls include low liquid assets, low illiquid assets, and unsecured debt dummies. Coefficients reported in columns (1)-(3). Average marginal effects reported in columns (4)-(6).