Can’t Pay or Won’t Pay? Unemployment, Negative Equity, and Strategic Default

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This paper uses new data from the PSID to quantify the relative importance of negative equity versus ability to pay, in driving mortgage defaults between 2009 and 2013. These data allow us to construct household budgets sets that provide better measures of ability to pay. Changes in ability to pay have large estimated effects. Job loss has an equivalent effect on the propensity to default as a 35% decline in equity. Strategic motives are also found to be quantitatively important, as we estimate more than 38% of households in default could make their mortgage payments without reducing consumption. (*JEL* D12, D14, E24, E30, E51, E60, G21 G33, L85, R31)

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A large literature has studied the determinants of residential mortgage default, with a focus on the extent to which default occurs among borrowers who have the ability to pay their mortgage, but who choose to default for what are called strategic reasons related to negative equity, compared to default

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among borrowers who simply do not have the ability to pay their mortgage. Understanding the relative importance of these determinants of default is central for designing policies aimed at reducing the probability of a future wave of mortgage defaults and foreclosures, and for designing loss mitigation policies that reduce the negative economic impacts of future possible foreclosure crises on lenders and homeowners (see, e.g., Chatterjee and Eyigungor 2009; Foote et al. 2010; Adelino, Gerardi, and Willen 2013).

Measuring a borrower's ability to pay fundamentally requires detailed, household-level data on borrowers' economic attributes, including their income, their employment status, and their balance sheet, as well as their mortgage characteristics and payment status. However, previous studies have lacked data on many of these variables, and have either omitted variables from the analysis, or have used regional-level data to proxy for household-level data.

This paper makes two contributions to the literature. First, it uses new data from the Panel Study of Income Dynamics (PSID) and the PSID supplemental housing survey, which provide detailed data on borrower incomes, employment status, balance sheets, and consumption, matched with household mortgage data. These data allow us to construct household budget sets and thus, provide the most comprehensive measures of ability to pay within the literature. This in turn enables us to analyze the relative importance of strategic motives in mortgage default decisions, versus ability to pay, in considerably more detail than the existing literature. In particular, the analysis provides the first estimates of how changes in borrower ability to pay affects the likelihood of default. Moreover, we are able to address the important question of how changes in ability to pay interact with changes in equity in driving default decisions.

The second contribution of the paper is to systematically study not only defaulters, but those who pay their mortgage. As we describe below, our findings for both those who default and those who pay are critical for understanding the mortgage default process and designing loss mitigation policies.

We begin by classifying defaulting borrowers in terms of their ability to pay in order to quantify the extent of strategic default in the PSID. Strategic default broadly refers to defaulters who have the ability to pay, but who default because their home value has fallen below their loan amount (Mian and Sufi 2009). We develop a procedure to assess strategic default by first forming household budget sets, and then identifying the defaulting households with negative equity positions who could continue making their mortgage payments without having to reduce their consumption below a specific level. To assess the robustness of this procedure, we use three definitions of this reference consumption level, ranging from maintaining the same household consumption level in the previous year, to the level of subsistence consumption as defined by the Veteran's Administration (VA). We compare these reference minimum consumption levels to borrower residual income, which is the difference between household resources and the mortgage payment.

These budget set comparisons suggest that both strategic motives and the lack of ability to pay are important in understanding household default decisions. They also provide new and surprising findings regarding those who choose to pay. In particular, we find that nearly all very low equity borrowers remain current, and that many who have almost no ability to pay remain current. We identify strategic motives in about 38% of the defaulting households, as this group has the ability to pay their mortgage without reducing consumption from its predefault levels.

However, we also show that almost 30% of defaulting households have such low ability to pay that they would need to reduce consumption below subsistence levels to remain current on their mortgages, and that the remaining 33% of defaulting households would need to at least reduce consumption below predefault levels to remain current.

While strategic motives are quantitatively important among defaulting borrowers, the budget set comparisons for all borrowers show that nearly 96% of low equity borrowers with the ability to pay remain current. Moreover, we show that the vast majority of borrowers with very low ability to pay avoid default. Specifically, 80% of households that need to cut their consumption to subsistence levels to make their mortgage payments ("can't pay" borrowers) remain current on their payments. This finding provides a simple explanation for why lenders rarely negotiate preemptive mortgage modifications with even very high risk borrowers, since most of these borrowers continue to pay (Foote et al. 2010; Adelino, Gerardi, and Willen 2013).

Following this descriptive analysis, we quantify the relative importance of strategic motives versus ability to pay by analyzing how changes in home equity and in residual income affect the probability of default in a multivariate setting. We first fit linear probability and logit models of default on a rich set of covariates that allow us to control for a variety of economic and demographic factors.

To address some possible endogeneity issues, we next use the richness of the PSID to construct instruments for residual income and housing equity. To instrument for equity, we use state-level house price appreciation since the purchase of the house. Instrumenting for residual income is more challenging. We therefore use three sets of instruments, and assess the robustness of the results across these specifications.

We exploit the long time-series dimension of the PSID to construct household-level unemployment shocks to instrument for residual income. We focus on involuntary separations and control for previous unemployment spells to account for potential endogeneity concerns. The second and third instruments consist of two components that are motivated by previous research. The first component is a health disability shock to instrument for residual income, which follows Low and Pistaferri (2015). The second component is a Bartik-type state-level employment shock based on aggregate employment flows and industry shares.

All of our instruments are strong predictors of residual income, and deliver similarly large estimates of the causal effect of residual income on mortgage default. Our IV estimates indicate that a 10% decline in residual income raises the probability of default by between 1.1 and 2.5 percentage points.

To compare the magnitudes of residual income loss and changes in equity on default, we show that our baseline estimates indicate that head of household job loss has an equivalent effect on the likelihood of default as a 35% decline in home equity, and if both the head and spouse lose their job this has the same impact on default as a 55% decline in home equity. These point estimates are very stable when we restrict the analysis to only involuntary job loss spells.

Regarding the importance of strategic motives, while approximately 38% of defaulters do have the ability to pay, we find that the estimated likelihood of default among low equity borrowers with the ability to pay is fairly low. Specifically, our IV estimates indicate that an increase in the loan-to-value (LTV) ratio from 75% to 125% raises the default probability of a high residual income borrower from about 3% to about 5%. However, we find that an increase in the LTV ratio from 75% to 125% raises the default probability for a low residual income borrower from 10% to 17%. This finding highlights a quantitatively important interaction between ability to pay and borrower equity in the pay/default decision.

Taken together, these findings have implications for the design of policies. In particular, they indicate that policies designed to reduce foreclosure by reducing monthly mortgage payments can be very effective, because these policies raise residual income. This applies to both low and high equity households, with the relative effect on the default probability being larger for high equity (low loan-to-value ratio) households, but the absolute effect being higher for the low equity (high loan-to-value ratio) households.

1. Data

This section presents the data used in this analysis. A major innovation is the use of matched data on mortgage characteristics and payment status with borrower socioeconomic and demographic variables. These matched data advance the literature in a number of ways.

One advance is on the measurement of household ability to pay. Measuring ability to pay in the literature has been very limited, and consequently little is known about the importance of this factor. On the one hand, anecdotal and limited survey results suggest that major life events, such as job loss, illness, and divorce, are associated with mortgage default (see Cutts and Merrill 2008; Hurd and Rohwedder 2010). However, previous quantitative studies of default have provided only weak evidence on the importance of these events due to the lack of household-level income, employment, and balance sheet data.[1] This lack of household-level data has led many researchers to use aggregate unemployment rate data and divorce rate data as proxies for household-level income shocks (e.g., Deng et al. 1996; Deng, Quigley, and Order 2000; Elul et al. 2010; Bhutta, Dokko, and Shan 2011; Palmer (2015)). These studies have found only weak correlations between these aggregate measures and default. More recently, Gyourko and Tracy (2014) analyze micro-loan-level data with county-level unemployment rates as a control. However, they adjust regional unemployment rate controls for attenuation bias, and this adjustment indicates a significant relationship between adjusted unemployment rates and default. This evidence more broadly suggests a stronger relationship between income shocks and mortgage default than found in the earlier studies.

As described below, the combination of mortgage data with borrower information on income, employment status, balance sheets, and consumption enable us to measure ability to pay, and analyze its importance in the default decision in considerably more detail than in the previous literature.

Our enhanced measures of ability to pay also have important implications for defining and classifying strategic default. To see this, we note that the most prominent measures of strategic default in the existing literature are based on survey respondents who report whether or not they knew people who had the ability to pay their mortgage, but walked away from their homes during the crisis (Guiso, Sapienza, and Zingales 2013). In the Online Appendix, we provide a comparison of our strategic default estimates to those in the literature, including comparisons of samples and methodologies.[2] An important benefit of our approach is that it is scientifically reproducible across researchers, and thus can provide significant discipline in analysis. We therefore view this approach of classifying defaulters in terms of their ability to pay as an important advance relative to other studies.

1.1 Sample construction

The primary data used in this study come from the 2009, 2011, and 2013 PSID Supplements on Housing, Mortgage Distress, and Wealth Data. We restrict the sample to mortgagor heads between the ages of 24 and 65 who report being in the labor force or being disabled. We also restrict the sample to households with LTV ratios less than 250% that had not defaulted as of a prior survey.[3] These sample restrictions leave us with 7,404 households.[4]

1 To be clear, many administrative mortgage data sets include some information on income and employment at the time a loan is originated, but to our knowledge, none of these data sets include information on these variables after origination.

2 In the Online Appendix, we focus on three studies in particular: Experian and Oliver Wyman (2009), Guiso, Sapienza, and Zingales (2013), and Bradley, Cutts, and Liu (2015).

3 The LTV requirement drops what appear to be misreported mortgage and home values (the inclusion of these observations does not materially change the main results). Dropping households that reported being in default in a previous survey simply eliminates double counting.

4 In the Online Appendix, we compare the sample selection criteria with previous studies of mortgage default. Relative to the existing literature, the sample is quite broad and, as we will show in the following section, appears

1.2 Variable definitions and representativeness of the PSID data

This section summarizes how representative "are" the PSID data along several relevant dimensions of the analysis including household income, consumption, unemployment, mortgage characteristics, and mortgage default.

The unit of analysis in this study is the household. The household includes both the "head" and "spouse" as defined by the PSID, along with any children and other persons living in the primary residence. The primary measure of income is total household income, which is composed of the sum across household members of (1) wage and salary income; (2) transfer income (including social security, alimony and child support); (3) business income; and (4) interest and dividend income. This measure corresponds to the IRS definition of adjusted gross income less realized capital gains.[5]

Our measure of consumption includes expenditures on food, housing, clothing, health care, entertainment, and education. In the Online Appendix, we show how the PSID consumption measures compare to the Consumer Expenditure Survey (CEX) measures as tabulated by the Bureau of Economic Analysis (BEA) from 2009 to 2013. We find that in general, consumption levels are quite similar across the two data sets, and for most expenditure categories, the trends in consumption are also quite similar.

To measure unemployment, we use the fact that the PSID provides the employment status for both the head and the spouse over the previous calendar year as well as at the time of the interview. We discuss our exact unemployment variable definitions in detail in Section 3.2, where we present the results from our empirical models. Using the measure of employment status at the time of the survey yields an unemployment rate of 5% in our sample of mortgagors. For the years in question (2009, 2011, and 2013), the average of the headline unemployment rate reported by the Bureau of Labor Statistics was 8.5%.[6]

The PSID provides information (i.e., interest rates and amounts) on all liens on the household's principal residence (1st and 2nd mortgages). In addition, the survey includes the respondent's estimate of the current market value of the principal residence. Table 1 compares mortgage statistics from our PSID sample with data from the 2009, 2011, and 2013 National American Housing Survey (AHS).[7] In general, mortgage characteristics are quite similar across the two data sets. The median outstanding principal balance, monthly mortgage payment, mortgage interest rate, remaining maturity, and LTV ratio (calculated

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to be representative of the population of mortgagors. It includes both fixed-rate and adjustable-rate mortgages, as well as older origination cohorts that have accumulated significant amounts of equity in their homes.

5 In the Online Appendix, we compare our PSID measure of average family income to what is reported by the Census and show that they are very similar.

6 It is well known in the literature that homeowners are less likely to experience an unemployment spell compared with renters. This likely explains a significant portion of this gap.

7 The AHS is biennially conducted by the U.S. Census Bureau. It has a sample size of about 50,000 housing units and is designed to provide representative data on the U.S. housing and mortgage markets.

Table 1
Comparing PSID and American Housing Survey mortgage data: 2009–2013

	2009		2011		2013	
	PSID	AHS	PSID	AHS	PSID	AHS
Median:						
Unpaid balance ($)	120,000	106,909	120,000	120,000	130,000	121,324
Interest rate (%)	5.0	6.0	5.0	5.3	4.0	4.5
Years remaining	24	23	22	22	21	21
Monthly payment ($)	1,100	878	1,100	1,015	1,085	997
LTV ratio (1st lien %)	65	63	68	71	69	70
Fraction with:						
Second mortgage	0.21	0.21	0.18	0.13	0.15	0.10
ARM	0.09	0.06	0.08	0.07	0.08	0.06
Observations	2,640	51,969	2,462	49,734	2,295	47,741

This table compares mortgage summary statistics in the PSID and AHS surveys. AHS 2009 National Statistics are taken from tables 3.13 and 3.15. AHS 2011 and 2013 National Statistics are taken from table C-14A-OO. The PSID sample consists of household heads who are mortgagors, aged 24–65, and labor force participants (including those who are disabled) with combined LTV ratios less than 250% in the 2009, 2011, and 2013 surveys. Households that report being in default in a given year are subsequently dropped to avoid double counting.

for first liens only) are all extremely close in both data sets. Finally, the fractions of households with second mortgages and adjustable-rate mortgages (ARMs) are also similar across the two data sets.

Information on mortgage performance in the PSID is available beginning in the 2009 survey.[8] Households were asked how many months they were behind on their mortgage payments at the time of the PSID interview. In the empirical analysis below, we adopt a default definition that corresponds to two or more payments behind (at least 60 days delinquent), which is standard in the literature.[9]

Most researchers studying mortgage default use large, loan-level administrative data sets so a natural question is how the PSID compares. At first glance default rates in the PSID appear to be significantly lower than those found in administrative data sets like McDash, a nationally representative, loan-level mortgage servicing data set that has been used by many researchers. Below, we will show that the differences are completely eliminated by focusing on primary residences and by matching the distribution of LTV ratios.

In Table 2, we compare default rates in the PSID to those in McDash/Equifax,[10] a data set that consists of McDash, matched to credit bureau data from Equifax at the borrower level.[11] Using comparable definitions

8 There is some information on mortgage characteristics in PSID surveys prior to 2009, but there is no information on mortgage performance.

9 Information on missed payments is only provided at the time of the interview, making it impossible to measure the exact timing of the first missed payment. This means that we cannot identify, for example, borrowers who missed two or more payments at some point in the previous calendar year but cured by the time of the interview.

10 The official name is CRISM (Equifax Credit Risk Insight Servicing McDash Database).

11 The matching process was conducted by Equifax using confidential and proprietary data. Coverage begins in 2005, and according to Equifax, approximately 90% of LPS mortgages were matched to a credit bureau account with high confidence.

Table 2
Comparison of default rates in the 2009 PSID Survey and 2009 McDash/Equifax Database

	McDash/Equifax						**PSID with McDash/Efx. shares**	
	All properties		Primary residences only		**PSID**			
LTV category	Default rate	Share	Default rate	Share	Default rate	Share	Default rate	Share
All	**8.6%**		**5.4%**		**3.9%**		**5.4%**	
LTV $\geq$ 100	23.1%	21.8%	14.0%	20.7%	16.0%	10.5%	16.0%	20.7%
80 < LTV < 100	8.4%	24.2%	5.7%	24.2%	3.8%	18.8%	3.8%	24.2%
LTV $\leq$ 80	2.8%	54.0%	2.0%	55.1%	2.2%	70.7%	2.2%	55.1%

This table compares mortgage default rates and LTV distributions in the full, unrestricted, 2009 PSID survey, and a sample of loans from McDash matched to credit bureau data from Equifax in 2009. We define a property as a primary residence if (1) the borrower only has one first lien and (2) the ZIP code of the address reported to Equifax is the same as the ZIP code of the property reported to LPS. CRISM is a proprietary data set that contains credit bureau data on individual consumers' credit histories matched to LPS mortgage servicing data.

(default defined as at least 60 days delinquent on payments), we focus on default rates in a given year in the PSID with default rates in June of the same year for McDash/Equifax.[12] For space considerations, the table only displays results for 2009; however, in the Online Appendix, we show results for 2011 and 2013, which are very similar.

Table 2 shows a more than twofold difference in default rates across data sets: 8.6% of loans in McDash/Equifax are more than 60 days delinquent, whereas the comparable figure for the PSID is only 3.9%. What explains this gap? First, and most importantly, the measures of default in the PSID and LPS are not directly comparable. The PSID asks borrowers for the status of the loan on their primary residence while McDash asks lenders (or more precisely servicers) about the status of all loans in their portfolio, a set that includes loans on primary residences but also second homes, investor properties, and vacant homes, a category particularly relevant for delinquent loans. McDash/Equifax allows us to address this discrepancy using information from both the servicing and credit bureau components of the database. Specifically, we create a sample of loans on only primary residences by eliminating observations where McDash reports that the mortgage is associated with an investor or vacation property. We also use the presence of additional first liens reported in Equifax and we compare the address of the property and the address of the borrower to identify additional loans that are not secured by the borrower's primary residence. Eliminating these observations reduces the default rate in McDash/Equifax to 5.4% from 8.6% and the gap between default rates in the two data sets from a factor of 2.2 to a factor of 1.4.

The second major difference between McDash/Equifax and the PSID has to do with the distribution of LTV ratios. In the lower part of Table 2, we divide up our samples by the contemporaneous LTV ratio. Conditional on the LTV ratio, default rates in McDash/Equifax are no longer consistently

12 Most of the PSID interviews are conducted in the first half of the survey year.

higher than those in the PSID and are, in fact, quite comparable: 16% of borrowers in the PSID with a LTV ratio greater than 100 report being in default, whereas the comparable figure for McDash/Equifax is 14%. If the default rates are comparable conditional on the LTV ratio, why is the overall default rate 1.4% higher for McDash/Equifax? Table 2 shows significant differences in the distribution of LTV ratios: more than 20% of loans in McDash/Equifax have LTV ratios greater than 100% as compared to slightly greater than 10% in the PSID. In the right-most panel of the table, we conduct a simple counterfactual exercise and reweight the PSID results using the McDash/Equifax LTV distribution. The resultant default rate in the PSID is 5.4%, exactly the same default rate in the Primary Residence subsample of McDash/Equifax. In other words, the gap between the 8.6% default rate in the unrestricted McDash/Equifax sample and the 3.9% in the PSID can be explained entirely by focusing on primary residences and matching the LTV distributions.

From this exercise, we conclude that mortgage default rates in the PSID are largely representative of loans secured by borrowers' primary residences but that high LTV mortgages appear to be under-sampled in the PSID, especially in 2009 and 2011.[13] We address this issue in more detail in the Online Appendix by using the McDash/Equifax data to build a set of sample weights, which corrects for the undersampling of negative equity properties in the PSID. We show that the main empirical results in the paper are largely unchanged when we use these weights, which is unsurprising since either they are conditional on LTV ratios or they are stratified by LTV ratios.

1.3 Summary statistics

In Table 3, we provide summary statistics for our overall PSID sample as well as for the subset of mortgagor households who have defaulted on their loans. Panel A of Table 3 reveals several key facts about the distributions of income and consumption for defaulters versus the population as a whole. First, defaulters have much lower levels of income than the population as a whole. While the entire distribution of income is lower for defaulters, the table shows that some defaulters do have considerable income; 10% of defaulters have a pretax income of at least $130,000. Households in default are much more likely to report a decline in income, as the median defaulter reports a 7% decrease in income over the two previous years compared to a 6% increase in income for the median household in the full sample. In addition, 42% of defaulters have experienced a drop in income exceeding 15% compared to only 19% for the whole sample.

In panel B, we see that households in default are less educated and less likely to be married than the typical mortgagor. Panel B also shows that the age

[13] The LTV distributions in the PSID and McDash/Equifax are very similar in 2013. For more details, we direct the reader to the Online Appendix.

Table 3
Sample summary statistics for PSID household heads

	All mortgagor households				Households in default			
	Mean	10th. perc.	Median	90th perc.	Mean	10th perc.	Median	90th perc.
(A) Income and consumption:								
Real income ($1000s)	120	40	94	210	71	21	60	130
Real income after tax ($1000s)	87	34	72	150	58	23	53	110
Real total consumption ($1000s)	65	29	56	110	58	27	50	100
% Change in income (2yr period)	8	−31	6	59	−4	−55	−7	58
15% income drop or more (d)	0.19	0	0	1	0.42	0	0	1
30% income drop or more (d)	0.10	0	0	1	0.24	0	0	1
Log residual income	11.2	10.3	11.2	12.1	10.5	8.9	10.6	11.6
Residual income ($1000s)	100	28	77	180	50	7	42	110
(B) Demographics:								
Married (d)	0.70	0	1	1	0.55	0	1	1
College grad+ education (d)	0.45	0	0	1	0.23	0	0	1
Less than high school (d)	0.06	0	0	0	0.16	0	0	1
Age	46	31	46	60	45	31	46	59
(C) LTV and delinquency:								
LTV ratio	0.68	0.25	0.69	1	1.01	0.58	0.95	1.68
Default (60+ days late) (d)	0.03	0	0	0	1.00	1	1	1
Default (90+ days late) (d)	0.02	0	0	0	0.63	0	1	1
(D) Wealth:								
Liquid assets ($1000s)	26.0	0	6.2	57.0	4.6	0	0.5	5.4
Illiquid assets ($1000s)	15.0	3.1	27.0	35.0	36.0	0	7.6	57.0
(E) Employment and disabilities:								
Unemployed head last year (d)	0.070	0	0	0	0.220	0	0	1
Unemployed spouse last year (d)	0.040	0	0	0	0.100	0	0	1
Unemployed head or spouse last year (d)	0.110	0	0	1	0.280	0	0	1
Invol. unemployment, head (d)	0.027	0	0	0	0.104	0	0	1
Invol. unemployment, spouse (d)	0.007	0	0	0	0.006	0	0	0
Trans. into disability, head (d)	0.040	0	0	0	0.060	0	0	0
Trans. into disability, sp. (d)	0.036	0	0	0	0.056	0	0	0
Trans. into severe disability, head (d)	0.015	0	0	0	0.051	0	0	0
Observations			7,404		248			

This table displays summary statistics for the sample of PSID households surveyed in 2009, 2011, and 2013. Default is defined as 60+ days late as of survey date (at least two missed payments). The sample includes heads of household who are mortgagors, aged 24–65, and labor force participants (including those who are disabled) with combined LTV ratios less than 250%. Households that report they are in default in a given year are subsequently dropped to avoid double counting. All $ values are deflated by the 2013 CPI. PSID weights are used to calculate all summary statistics unless otherwise noted. Dummy variables are signified by (d).

distribution for defaulters and nondefaulters is quite similar. Panel C shows that the distribution of LTV ratios is significantly higher for defaulters, a fact that has been well-documented in the literature. In panel D, we can clearly see that defaulters also have significantly less wealth. The median defaulter has only $518 in liquid assets compared to the median household in the sample that has more than $6,000.[14]

Finally, panel E of Table 3 displays information on unemployment spells and disability shocks. It is clear from the panel that households in default are much

14 Liquid assets include checking and savings accounts, money market funds, certificates of deposit, government savings bonds, and Treasury bills. Illiquid assets include equity and bond holdings, the value of automobiles, retirement accounts, and business income. Housing equity is not included in the measure of illiquid assets.

more likely to have experienced a spell of unemployment. As of the survey date, 7% of the full sample of household heads report being unemployed compared to 22% of the sample of defaulters. A similar pattern emerges for households that have experienced a disability, especially a severe disability. Only 1.5% of household heads in the full sample report having suffered a severe disability since the previous interview, compared to more than 5% of defaulters reporting a severe disability, while the broader disability variable (which includes moderate disabilities, as well as severe disabilities) is 4% of household heads, compared to 6% for defaulters.[15]

2. Mortgage Affordability and Strategic Default

Since the mortgage foreclosure crisis that occurred in 2007 the concept of strategic default has become a popular topic in the economics and finance literature. A major limitation of this literature however, is the lack of an economic framework to help distinguish between borrowers who strategically default and those who do not. As a result, there is significant disagreement about how to define strategic default, which has predictably led to very different estimates of its importance in the mortgage market.

In this section, we develop a definition of strategic default that is linked to the economic concept of affordability. In the first part of the section, we establish a simple method for classifying mortgage payments into those that are "affordable" and those that are "unaffordable" and show that this classification yields significant differences in default rates across borrowers. In the final part of the section, we relate this classification to the notion of strategic default and use our PSID data to quantify its importance.

2.1 Identifying "can pay" and "can't pay" borrowers

We begin by proposing a classification system for mortgage defaults using a standard household budget constraint. Specifically, we define cutoffs for "unaffordable" and "affordable" mortgage payments based on the amount of disposable income available for a household to consume. Let c denote household spending on nonhousing consumption in the year of default and h denote housing expenditures, which are financed with a mortgage with required payment, m. Assuming, for now, that a household has no wealth and cannot borrow in unsecured credit markets, the household budget constraint is given by

$$c+h \leq y. \tag{1}$$

The household is faced with a choice of either making the mortgage payment m or defaulting, experiencing foreclosure, and subsequently paying rent r for a

[15] The Online Appendix provides a detailed description of how we construct disability shocks.

new home.[16] Given a choice of m or r, the household's residual income, $y-m$ or $y-r$, respectively defines its consumption, meaning that the household is choosing between the combination of paying the mortgage and consuming $y-m$ versus defaulting and consuming $y-r$. We assume that $m>r$ so a borrower can always increase nonhousing consumption by defaulting. Even with perfect information about y, m and r, we cannot answer the question of whether a borrower should default without information about preferences, for example, over renting versus owning, or beliefs about the evolution of future house prices. But, even without such information, one can ask about the effect of residual income on the decision to make the mortgage payment and that is our focus in this section.

First, we define a mortgage as being *unaffordable* if the payment m leads to residual income that is below a subsistence level of consumption. We call this level c_{VA} because we use the Veteran's Administration (VA) rules to measure subsistence. Formally,

$$\text{Unaffordability} \Leftrightarrow y-m<c_{VA}.$$

Intuitively, regardless of preferences, a mortgage payment is unaffordable if the household is unable to meet its basic necessities with its residual income.

Second, we define a mortgage as *affordable* if the household can maintain its level of consumption from the previous year c_{-1}, where we are assuming that the household chose not to default in the previous year.[17] Formally,

$$\text{Affordability} \Leftrightarrow y-m \geq c_{-1}.$$

That the household can maintain its prior consumption level, while paying the mortgage, captures the popular notion of a borrower who "can afford his or her mortgage." It is important to note that our definitions are not exhaustive as a mortgage could be neither unaffordable nor affordable if $c_{VA}<y-m<c_{-1}$, meaning that residual income is high enough to maintain consumption above subsistence levels, but not high enough to maintain the previous levels of consumption.[18]

While this is a simple framework to classify borrowers it is difficult to operationalize. To do so requires detailed data on both household consumption and income, in addition to mortgage debt, which previous studies on the topic have lacked. Fortunately, all of these variables are available in the PSID data. Our measure of household income, y, is the monthly average of after-tax

[16] A foreclosure severely affects an individual's credit score for 7 years in the United States, making it extremely difficult to obtain another mortgage to purchase a home during that period.

[17] Recall from our discussion above that only first-time defaults are retained in the sample. We also tried using consumption lagged 2 years, c_{-2}, and found very similar results.

[18] It is possible for consumption to be *both* affordable and unaffordable if $c_{VA}>c_{-1}$, but we show that this is extremely rare in our data.

income of the family unit, measured over the previous calendar year.[19] Our measure of m is the sum of all mortgage payments, property taxes, and insurance associated with the family unit's primary residence. c(VA) is a subsistence level of consumption defined by the VA that depends on the size and geographical location of the household.[20] Our measure of consumption, c_{-1}, is the average monthly expenditures of the household, excluding mortgage related expenses, which is, as with income, measured over the previous calendar year.

Table 4 displays a set of simple cross tabulations using these definitions. In panel A, Column (1), we see that about 70% of all households in the sample have mortgage payments that are affordable based on our above classification. We refer to these households as "can pay."[21] In contrast, approximately 7% have unaffordable mortgage payments (i.e., their residual income is less than VA subsistence levels), and we refer to these as "can't pay" households (Column (3)). In Column (2), we see that approximately 23% of households are in-between, meaning that they have enough income to pay their mortgages and consume more than subsistence levels, but not enough to maintain their previous levels of consumption. In panels B and C of Table 4, the sample is stratified by LTV ratio. High LTV households ($LTV > 90$) are slightly less likely to be "can pay" and slightly more likely to be "can't pay" compared to low LTV households ($LTV < 90$).

The default rates in Table 4 show that the can pay/can't pay distinction has power. Focusing on panel A, Column (1) shows that out of more than 5,000 "can pay" households, only 1.4% (74) default. In contrast, of the 531 "can't pay" households, 10.7% (57) default, which implies that "can't pay" borrowers are approximately 7 times more likely to default than "can pay" borrowers. Dividing the sample into high and low LTV samples yields even more dramatic differences. The least risky subsample, "can pay" households with low LTV ratios, account for more than half the sample (55%), and the table shows that

19 Ideally, we would like a measure of residual income at the time of the survey to be consistent with the timing of our mortgage default variable. For this reason, we adjust income to account for the household's employment status at the time of the survey. Specifically, if the head of household is not employed as of the survey date, we reduce y by the average monthly labor earnings of the head. If the spouse is not employed as of the survey date or the head was recently divorced, we reduce y by the average monthly labor earnings of the spouse. We do not make this adjustment in our regression analysis in Section 4 since doing so would introduce a mechanical correlation between our measure of residual income and the unemployment instruments that we employ. We make no adjustment for households who are employed at the time of the survey, so for these households residual income is measured with a lag relative to their default decision. However, this timing discrepancy is unlikely to be a major issue as the vast majority of PSID interviews (about 80%) take place within the first 6 months of the calendar year.

20 For more details, see "Lenders Handbook - VA Pamphlet 26-7," ch. 4 on underwriting loans, which is available online at `http://www.benefits.va.gov/warms/pam26_7.asp`. This includes the VA definition of residual income as "Residual income is the amount of net income remaining (after deduction of debts and obligations and monthly shelter expenses) to cover family living expenses such as food, health care, clothing, and gasoline" (p. 55).

21 The difference in the number of observations for defaulting households is the result of weighting. Specifically, there are 248 raw defaults, and 196 is the weighted equivalent number of defaulters. Because of rounding, the row sums of Table 4 do not necessarily sum to the total. The Online Appendix includes an unweighted version of the table.

Table 4
Measures of strategic default: How many defaulters can afford their payments?

	(1) **"Can pay"** $c < y - m$		(2) $c > y - m > c(VA)$		(3) **"Can't pay"** $y - m < c(VA)$		(4) Total
	# (i)	share (ii)=(i)/(vii)	# (iii)	share (iv)=(iii)/(vii)	# (v)	share (vi)=(v)/(vii)	# (vii)
A. Total							
Default	74	0.377	65	0.333	57	0.291	196
Population	5,173	0.699	1,704	0.230	531	0.072	7,404
Default rate (# Def./# Pop.)	0.014		0.038		0.107		0.027
B. LTV > 90							
Default	47	0.409	41	0.352	28	0.239	115
Population	1,117	0.664	428	0.254	140	0.083	1,684
Default rate	0.042		0.095		0.197		0.069
C. LTV < 90							
Default	27	0.330	25	0.306	29	0.364	81
Population	4,056	0.709	1,277	0.223	391	0.068	5,720
Default rate	0.007		0.019		0.075		0.014

This table displays statistics on strategic default measures calculated from the PSID. Income, y, is defined as average monthly after-tax family income. If the head of household is unemployed as of the survey date, then the head's labor earnings for that month are set to zero (likewise for the spouse). If the head is recently divorced, then spousal labor earnings are set to zero. Consumption, c, is defined as average monthly expenditures, and m is the monthly mortgage payment across all mortgages, plus associated property taxes and insurance. VA subsistence consumption is defined using the VA residual income based on the region, number of children, and size of the mortgage as of the survey date.

only 0.7% of these borrowers default. In contrast, the most risky subsample, "can't pay" households with high LTV ratios, have a default rate approaching 20%. In other words, based solely on the ability to pay variables and LTV dichotomy we can identify groups with a thirtyfold difference in default rates.

Comparing differences in default rates also yields important insights. First, the likelihood of default is very low for low LTV households—as Column (4) shows, only 1.4% default—but for the "can't pay" subsample of low LTV households the default rate soars to 7.5%, which is more than 10 times the default rate of "can pay" low LTV households. This is intuitive since the essence of "can't pay" is that the borrower simply does not have the cash flow necessary to make the mortgage payments and maintain a minimal level of consumption. The fact that the household could enjoy a positive income shock or sell the house in the future does not matter, whereas for the "can pay" household, there is little point in defaulting as it has the cash flow necessary to make the payment without needing to sacrifice a significant amount of consumption. As one would expect, for the high LTV households, the effect of ability-to-pay on differences in default rates is smaller than for low LTV households (a fivefold difference instead of a tenfold difference).

While Table 4 is consistent with an important role for ability-to-pay, it also illustrates the limits of the framework. As discussed above, the fact that we find a thirtyfold difference in default rates between "can't pay" borrowers with high LTV ratios and "can pay" borrowers with low LTV ratios illustrates the importance of ability-to-pay. However, the flip-side of the fact that 20% of the "high-risk" households default is that 80% of them continue to make their payments. Indeed, the use of the phrase "can't pay" to describe a subsample of the population in which almost 90% (if we look at the whole sample including both high- and low-LTV households) *do* pay is, in a sense, a contradiction in terms. The issue is that while "ability-to-pay" is an easy concept to talk about it is not an easy concept to formalize. Equation (1) seems intuitive, but, it is based on the assumption that households must finance their current spending entirely out of current income. In reality, households can, potentially, finance spending either by borrowing or by drawing down accumulated savings. In other words, a more realistic version of Equation (1) would look like

$$c+m \le y+a+b, \tag{2}$$

where a is accumulated financial assets (i.e., wealth) and b is the maximum amount of (unsecured) credit that a household can access. Moving to such a formulation is not easy, especially in the context of strategic default. It seems reasonable to call a default strategic if a household has free cash flow that exceeds the cost of the mortgage. However, would it be equally appropriate to call a default strategic if the household could only "afford" the mortgage payment by drawing down its retirement savings or borrowing on credit cards? In other words, is default strategic unless the household has exhausted all of its savings and borrowed up to the maximum amount available on all available credit lines?[22]

Although we cannot tell for certain, it seems reasonable that the "can't pay" households that *do* pay are using some combination of borrowing and drawing down savings, perhaps augmented by resources from their extended family. In principle, one could answer this question with data, but to assess the sources of funds for payments, one would need much higher frequency wealth information than the biennial data from the PSID.[23]

2.2 Quantifying strategic defaults

The discussion above links the concept of affordability to mortgage default in a manner that makes it a natural definition for what has been termed "strategic" or "ruthless" default in the literature. The idea is that a household that chooses to default on its mortgage debt while having the ability to make its mortgage payment and maintain its level of consumption, has made a strategic

[22] Adding more nuance here, by expanding the budget constraint, one could argue that a "can pay" household is diverting money from saving and, therefore, future consumption by making its monthly payment. If along some future path, such a lack of saving results in destitution, then some "can pay" households, as we have defined them, really cannot afford their mortgage payments.

[23] In the Online Appendix, we incorporate information on assets and liabilities in the PSID to create a version of Table 4 that is based on Equation (2). The results are broadly similar.

decision. Such a definition is internally consistent with standard models of defaultable debt, as well as the popular notion of "ruthless" default, whereby a borrower defaults for purely investment considerations, as opposed to liquidity-related concerns. In this section, we use our classification of "affordable" and "unaffordable" mortgage payments to quantify the extent of strategic default in the data.

Column (1) of panel A of Table 4 shows that 38% of the households in default have affordable mortgages, in the sense that they could make their mortgage payment without reducing their consumption, implying that almost 40% of defaults in the sample are strategic. Column (3), however, shows that only 29% of mortgages are unaffordable in the sense that household consumption would drop below subsistence levels if payments continue to be made. Thus, the number of strategic defaults depends on exactly how one defines affordability. If one adopts the broad idea that a mortgage is only affordable if making the mortgage payment requires no reduction in household consumption, then the share of strategic defaults, 38%, is comparatively small. But using this definition implies that all other consumption takes priority over the mortgage. For example, if paying the mortgage requires that the household replace a luxury car with a more modest alternative, this definition would say that the household cannot afford the mortgage. At the other extreme, if one adopts the much stricter idea that a mortgage is unaffordable if making the mortgage payment will lead to a level of consumption that is below subsistence, then a comparatively large fraction of defaulters, 71%, are strategic.

Panels B and C show that strategic default is somewhat more common, using either definition, for high LTV ratio borrowers and less common for low LTV ratio borrowers. Whereas for the whole population, our strategic default estimates ranged from 38% to 71%, for the high LTV sample, they range from 41% to 76% and for the low LTV ratio sample from 33% to 64%. The response to the LTV ratio is consistent with the idea that high LTV ratios make households more likely to default even when they can afford their monthly payments.

In the Online Appendix, we consider an alternate definition of affordability based on the Qualified Residential Mortgage (QRM) guidelines, and find consistent estimates of strategic default.

3. Default and Residual Income

The analysis in Section 2 strongly suggested that many households default because they do not have the financial resources to continue making their periodic mortgage payments. For example, approximately 29% of households in default do not have enough residual income to meet their basic consumption needs, and an additional 33% of defaulters do not have enough residual income to maintain their predefault consumption levels. While illustrative, that analysis is entirely descriptive in nature. In this section, we attempt to measure the causal impact of residual income on mortgage default.

We begin by showing that the correlation between low residual income and mortgage default is very strong in the data, even after controlling for potentially confounding variables including housing equity, a detailed set of mortgage characteristics, geographic factors, and a detailed set of household demographic characteristics available in the PSID. We then use the richness of the PSID data to construct instruments for residual income and housing equity to directly address potential endogeneity bias. Our choice of instruments is based on the idea that negative shocks to household-level income should result in low residual income levels. We show that this is clearly the case in the data, as households in the bottom of the residual income distribution are much more likely to have experienced a recent negative income shock compared to those in the top of the distribution. It then follows that any exogenous shock that affects household income is a good candidate for an instrument for residual income. We focus on two plausibly exogenous shocks: involuntary unemployment spells and disability.

3.1 Ordinary least squares and logit results

The analysis begins with ordinary least squares (OLS) and logistic multivariate regression estimates of mortgage default on residual income, where we condition on a detailed set of household demographic characteristics, mortgage characteristics, as well as geographic controls (at the state level). Residual income is calculated using gross (before tax) household income that excludes capital gains, but includes all other sources of income including income from operating a business (see Section 1 for more details) less total mortgage expenses, including the first and second mortgage. We focus on the (natural) logarithm of residual income, in order to capture a potential nonlinear relationship due to the existence of subsistence consumption levels.[24] A minimum level of consumption that is required for survival, implies that the same increase in residual income for a household with very low levels of income should have a larger impact on its default decision compared to the decision of a household with very high levels of income.[25,26]

Table 5 displays the baseline results. Columns (1)–(3) display OLS regression estimates (i.e., linear probability models) of an indicator of mortgage default (at least 60 days delinquent) on residual income, and Columns (4)–(6) repeat

24 There is a small issue in specifying the logarithm of residual income as a few households in our data have negative values of residual income. To deal with this issue, we winsorize the residual income variable choosing a threshold that corresponds to the first percentile of the residual income distribution ($3,810). We have experimented with alternative thresholds and find that the results reported below are not sensitive to this particular choice.

25 By taking the log of residual income, we are assuming that the impact of residual income on default is proportional. For example, the impact on default of an increase in residual income of $50 for a household that starts with only $100 in residual income will be the same as an increase in residual income of $5,000 for a household that starts with $10,000 in residual income.

26 In the Online Appendix, we consider alternate specifications, including the ratio of m to y (i.e., the debt-to-income ratio), and show that the baseline results are robust. Furthermore, in the Online Appendix, we consider income changes and show that the baseline results are robust.

Table 5
Baseline results: Linear probability and logit models

	OLS			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
LTV ratio	0.071***	0.078***	0.680***	1.798***	1.755***	−1.446
	(7.61)	(6.74)	(4.34)	(10.34)	(8.93)	(−0.77)
				[0.054***]	[0.051***]	[0.051***]
Log residual income	−0.037***	−0.025***	0.012	−0.932***	−0.727***	−0.993***
	(9.73)	(5.74)	(1.32)	(14.01)	(8.19)	(5.90)
				[−0.028***]	[−0.021***]	[−0.021***]
Log residual income x LTV ratio			−0.055***			0.305*
			(3.97)			(1.74)
						[−0.0194***]
Constant	0.399***	0.190***	−0.218**	5.289***	1.105	3.852*
	(9.03)	(3.70)	(2.06)	(7.12)	(0.73)	(1.82)
Observations	7,404	7,404	7,404	7,404	7,404	7,404
R^2	0.05	0.08	0.08	0.13	0.19	0.19
Demographic controls?	N	Y	Y	N	Y	Y
Mortgage controls?	N	Y	Y	N	Y	Y
State controls?	N	Y	Y	N	Y	Y

This table displays OLS estimation results of regressions of default on LTV ratios and residual income in Columns (1)–(3). Columns (4)–(6) report logit coefficients, and the terms in square brackets are the average marginal effects. To compute the interaction we compute the difference in the LTV AME between the interquartile range of residual income. Residual income is defined as gross family income less mortgage expenses. Default is defined as 60+ days late as of survey date (at least two missed payments). The sample includes all household heads in the PSID who are mortgagors, aged 24–65, and labor force participants (including those who are disabled) with combined LTV ratios less than 250%. Robust t-statistics are reported in parentheses. Level of statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

the exercise using logistic regressions. Columns (1) and (4) do not include any controls, whereas the remaining columns include numerous demographic, state-level, and loan-level controls.[27] All columns include the household's (self-reported) LTV ratio at the time of the survey, as the prior literature has documented that home equity is a strong predictor of default.

The OLS coefficients associated with the logarithm of residual income should be interpreted as semi-elasticities. Thus, according to Column (1), a 10% decrease in residual income is associated with a decrease in the likelihood of default of approximately 0.37 percentage points. In Column (2), we see that the magnitude of the semielasticity drops somewhat when we include the control variables, but is still negative and statistically significant. In Column (3), we include an interaction between the household's LTV ratio and residual income. This specification is motivated by the double-trigger theory of mortgage default, which predicts that the combination of liquidity shocks and declines in home

27 The demographic controls include 1-digit industry, year, race, education, marital status, and gender indicator variables, as well as the age of the head of household and the number of children in the household. The mortgage controls include the mortgage interest rate as well as dummy variables for origination years, whether the mortgage is refinanced, the presence of a second mortgage, and whether the term remaining is >15 years. The state controls include indicator variables signifying if the state has a judicial foreclosure process, if the state allows lender recourse, and if the state is one of the "sand" states (Arizona, California, Florida, and Nevada) that experienced an especially dramatic housing boom and bust during the 2000s. In addition, changes in state-level house prices and unemployment are included. The Online Appendix includes a complete list and summary of the baseline set of controls.

values generates large increases in mortgage defaults.[28] The interaction term coefficient is negative and statistically significant, which means that for higher LTV ratios (lower equity levels), decreases in residual income have more pronounced effects on default. For example, at an LTV ratio of 1 (no equity), a 10% drop in residual income will increase the default rate by 0.43 percentage points (=$(-.1)^*.012-.055^*1^*(-.1)$), while at an LTV ratio of 1.5 (negative equity), a 10% drop in residual income increases the default rate by 0.7 percentage points (=$(-.1)^*.012-.055^*1.5^*(-.1)$).

The logit coefficients in Columns (4)–(6) are reported in the table without parentheses, while the standard errors are reported just below the coefficients (round parentheses), and the average marginal effects (AME) are reported below the standard errors (square parentheses). The average marginal effects in Columns (4) and (5) have the same sign and similar magnitudes to the OLS coefficients reported in Columns (1) and (2). Column (6) includes the interaction term between LTV ratio and residual income. Due to the nonlinearity of the logit model, the AME associated with the interaction must be calculated at discrete points in the state space. We find that the AME associated with the interaction term, computed as the difference in the AME of LTV ratio between the interquartile range of residual income, is about half of the magnitude of the corresponding estimate in the linear probability model. However, the magnitude of the interaction effect is sensitive to the points at which it is calculated, and in many instances the interaction effect is larger than the LPM model.

While the results in Table 5 support the findings in Section 2 and strongly suggest that residual income plays an important role in household-level mortgage default decisions, they are still descriptive in nature. Income is not randomly assigned, but is instead determined by decisions consciously made by the household as well as some outside, exogenous forces. Therefore, in order to make any causal inferences about the effect of residual income on default, valid instruments are needed. As we mentioned above, our instrumental variables approach exploits the fact that many households with low residual income suffered major adverse shocks.

Table 6 provides details on the incidence of adverse shocks by quintile of residual income. The first row in the table shows that households in the bottom of the distribution are much more likely to have experienced a significant (30% or greater) drop in income since the previous interview compared to those in the top of the distribution. The next row in the table shows that unemployment is an important shock that leads to residual income differences as household heads in the bottom quintile of the distribution are more than three times as likely to report a recent unemployment spell compared to those in the top quintile. There is also evidence in the table that disability shocks play a role in generating variation in residual income across households. We exploit these

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

Table 6
Adverse shock incidence by residual income quintile

	Quintile of residual income				
	1	2	3	4	5
Income loss ≥ 30% (d)	25.6%	12.2%	5.9%	4.7%	3.9%
UE shock, head (d)	13.9%	7.1%	4.9%	4.0%	4.2%
UE shock, spouse (d)	4.3%	6.1%	5.7%	3.2%	3.1%
Disability shock, head (d)	6.0%	4.3%	3.7%	3.4%	2.7%
Disability shock, spouse (d)	3.4%	3.9%	3.4%	3.6%	3.8%
Any shock (UE, disability, or ≥ 30% income loss) (d)	40.9%	28.5%	20.0%	16.8%	16.1%

This table displays the fraction of households suffering a shock, split by quintile of residual income (defined as gross family income less mortgage expenses) for the sample of PSID households surveyed in 2009, 2011, and 2013. An unemployment (UE) shock is defined as an unemployment spell experienced in the 12 months before the PSID interview. A disability shock is defined as a transition into a state of disability since the previous PSID interview. Dummy variables are signified by (d).

patterns below to generate plausibly exogenous instruments for household-level residual income.

3.2 IV estimates based on unemployment shocks

Since unemployment spells are typically associated with significant income losses,[29] even accounting for unemployment insurance benefits, the literature has focused on unemployment as a potentially important driver of mortgage default. However, because of data limitations, previous studies used aggregate unemployment (at the state, MSA, or county aggregation level),[30] and have found only weak correlations between unemployment and mortgage default.[31] The PSID asks detailed questions about employment and unemployment spells, which allow us to construct household-level unemployment shocks.

We define an unemployment shock as corresponding to a household head who reports being unemployed at the time of the PSID survey or who reports a spell of unemployment over the 12 months prior to the survey date. We also construct a spousal unemployment shock using the same definition. However, there are potential concerns that these shocks are not entirely exogenous to the household and more importantly to the decision of the household to default on its mortgage. For example, some unemployment spells are voluntary and initiated by the employee. If the same underlying factors (unobservable to us) that drive households to leave their jobs also drive them to default on their loans, then we would mistakenly attribute income loss from unemployment shocks to be driving increased mortgage default.

We address this potential endogeneity bias in a few ways. First, we isolate job losses due to involuntary separations, which are defined in the PSID to be

29 See Saporta-Eksten (2014) and the papers cited therein.

30 For example, Deng, Quigley, and Order (2000) include state-level unemployment rates in their mortgage default and prepayment models, and Demyanyk and Van Hemert (2011) include county-level unemployment rates as controls in their analysis of subprime mortgage defaults.

31 See Gyourko and Tracy (2014) for a detailed discussion of how using aggregate unemployment rates as proxies for individual shocks could mask the true relationship between unemployment and mortgage default.

either plant closures, strikes/lockouts, or layoffs. Involuntary unemployment spells are less likely to suffer from endogeneity bias since they are events that occur outside of the purview of the household. However, there could still be a concern that there is some unobserved heterogeneity across households that drives both involuntary job separations and default decisions. For example, perhaps impatient households who heavily discount the future might be more likely to default on debt and may also be more likely to be fired due to poor work habits. If this unobserved factor does not vary over time, then the panel dimension of the PSID allows us to address the issue. To do so we construct indicator variables based on the number of prior unemployment spells over the seven PSID surveys spanning 1994 to 2005, and include these variables in our control set ("Job Loss FEs"). If there is a time-invariant factor that causes both an increased propensity to experience job loss and an increased propensity to default, this additional control should take care of the issue. In addition to these measures, we follow the labor economics literature and construct a completely different employment-based instrument based on national-level industry employment flows and state-level industry shares, which we discuss in Section 3.3.

In addition, we also need to address the potential endogeneity of the LTV variable. The LTV variable is the ratio of the self-reported remaining mortgage balance to the self-reported value of the house, and thus, corresponds to the household's estimate of its current equity position in the property. The total size of the mortgage and downpayment fraction at the time of origination are decisions made by the household.[32] These decisions may be correlated with some unobserved factors that are also correlated with the default decision, resulting in endogeneity bias. The example of heterogeneity in impatience discussed above is also applicable here as more impatient households are more likely to choose lower downpayments (i.e., higher LTV ratios at origination) and are also more likely to default on their debts. To address this issue we construct an instrument for the LTV ratio that corresponds to the cumulative growth in the state-level housing price index from the year of home purchase to the current interview year. The PSID provides the state in which the household resides, and using the panel aspect of the PSID, we can identify the exact year when the household purchased its current home. Cumulative house price appreciation at the state level is plausibly exogenous to the household's mortgage default decision, but should be correlated with the LTV ratio variable.[33]

Table 7 displays the results of the instrumental variables analysis. Column (1) in the table corresponds to the simple OLS estimates, which are replicated

[32] In addition, the decision on how much mortgage debt to pay down over time is also under the household's control.

[33] The assumption that is required for cumulative house price growth at the state level to be a valid instrument is that the timing of home purchase and the choice of state to reside in is exogenous with respect to the mortgage default decision.

Table 7
IV results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LTV ratio	0.078***	0.189***	0.150***	0.224***	0.154***	0.188***	0.149***	0.192***	0.150***
	(6.74)	(3.63)	(3.16)	(3.45)	(3.25)	(3.65)	(3.14)	(3.73)	(3.15)
log residual income	−0.025***	−0.149***		−0.240**		−0.109**		−0.116**	
	(5.74)	(4.47)		(2.35)		(1.97)		(1.97)	
Unemployed head last year (d)			0.053***						
			(4.14)						
Unemployed spouse last tear (d)			0.030**						
			(2.33)						
Involuntary unemployment, head (d)					0.055**				
					(2.54)				
Involuntary unemployment, spouse (d)					0.007				
					(0.28)				
Bartik instrument (2-yr. ch.)							−0.553		−0.536
							(0.86)		(0.83)
Transition into disability, head (d)							0.012		
							(0.89)		
Transition into disability, spouse (d)							0.033**		
							(2.33)		
Transition into major disability (d)									0.058
									(1.36)
Transition into major disability, spouse (d)									0.041
									(1.09)
IV for LTV:	. .	HPA since purchase	HPA since purchase	HPA since purchase	HPA since purchase	HPA since purchase	HPA since purchase	HPA since purchase	HPA since purchase
IV for income:	. .	Job loss head & spouse	.	Invol. job loss, head & spouse	.	Disability, Bartik shock	. .	Severe disability, Bartik shock	.
Observations	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404
Demographic controls?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mortgage controls?	Y	Y	Y	Y	Y	Y	Y	Y	Y
State controls?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Job loss FEs?	N	N	N	Y	N	N	N	N	N
J-test p-val null valid	.	0.58	.	0.28		0.18		0.63	
Weak ID p-val null weak	.	0	0	$1.66x10^{-4}$	0	$4.51x10^{-7}$	0	$1.18x10^{-7}$	0

This table displays a set of estimation from regressions of default on LTV ratios and residual income. Default is defined as 60+ days late as of survey date (at least two missed payments). Residual Income is defined as gross family income less mortgage expenses. Column (1) repeats Column (2) from Table 5. Column (2) uses unemployment over prior year for head and spouse as IV for residual income and cumulative state HP growth as IV for the LTV ratio. Column (3) is the reduced form of Column (2). Column (4) uses involuntary job loss as of the survey date as the income IV, and Column (5) is the reduced form of Column (4). Column (6) uses general disability shocks and a 2-year Bartik instrument as the income IVs, and Column (7) is the reduced form of Column (6). Column (8) uses severe disability shocks as the income IV, and Column (9) is the reduced form of Column (8). The demographic controls include 1-digit industry, year, race, education, marital status, and sex dummies as well as age and number of children. The mortgage controls include dummies for origination years, whether the mortgage is refinanced, the presence of a second mortgage, whether the term remaining is >15 years, whether or not the loan is refinanced as well as the interest rate. The state controls include whether the state is judicial, recourse, or one of the sand states, as well as changes in state-level house prices and unemployment. Job loss fixed effects are a set of dummies for the number of prior unemployment spells over the prior ten years to our study, from 1994 to 2005. Level of statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

from Table 5 (Column (2)) for ease of comparison. Column (2) in Table 7 displays the estimation results when we use the head and spouse unemployment shocks to instrument for income loss and cumulative house price appreciation to instrument for LTV ratios (all columns in the table use the same instrument for LTV ratios). There is a sizeable increase in the magnitude of the coefficient associated with residual income in the IV specification compared to the OLS regression. Households that suffer a 10% loss in residual income that is caused by an unemployment shock are approximately 1.5 percentage points more likely to default on their mortgages. This effect is an order of magnitude larger than the OLS estimate displayed in Column (1). The effect of the contemporaneous level of home equity on default also increases significantly when house price appreciation is used as an instrument, as the coefficient approximately doubles (from 0.078 to 0.189).

The increase in the estimated impact of residual income on mortgage default in the IV specification is both plausible and consistent with economic theory. The permanent income hypothesis predicts that permanent (or persistent) shocks to income have a significantly larger effect on consumption decisions compared to more transitory income shocks.[34] The IV specification isolates losses in residual income due to unemployment shocks, which can be significant life events and thus, are likely to have persistent effects. In other words, the IV specification is likely isolating more permanent income shocks, which theory predicts should lead to a much larger impact on the propensity to default. This is exactly what we find.

The first stage results are reported in Table 8. Cumulative house price appreciation is a very strong instrument for contemporaneous LTV ratios (panel A), and unemployment is a similarly strong instrument for residual income (panel B). In addition, estimates from the reduced form specification in which the default indicator is regressed directly on unemployment is displayed in Table 7 (Column (3)). Unemployment spells experienced by both the head of the household and the spouse are positively correlated with the incidence of default. Unemployed heads are approximately 5 percentage points more likely to default than employed heads, while households in which both the head and spouse experience an unemployment spell are more than 8 percentage points more likely to default. Head of household job loss has an equivalent effect on the likelihood of default as a 35% (.053/.15) decline in home equity, and if both the head and spouse lose their job this has the same impact on default as a 55% ((.053+.03)/.15) decline in home equity.

In Column (4), we substitute the unemployment variables with indicators of involuntary unemployment spells for both the head and spouse, and include a set of indicator variables corresponding to the number of prior involuntary unemployment spells to control for unobserved time invariant characteristics

[34] See Saporta-Eksten (2014) and Jarosch (2014) for job loss studies.

Table 8
IV results, first stages

A. LTV	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative state HP growth from purchase date	.	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***
	.	(14.54)	(14.54)	(14.70)	(14.70)	(14.54)	(14.54)	(14.51)	(14.51)
Unemployed head last year (d)	.	0.020	0.020						
	.	(1.48)	(1.48)						
Unemployed spouse last year (d)	.	0.026	0.026						
	.	(1.51)	(1.51)						
Involuntary unemployment, head (d)	.			0.025	0.025				
	.			(1.20)	(1.20)				
Involuntary unemployment, spouse (d)	.			0.013	0.013				
	.			(0.26)	(0.26)				
Bartik instrument (2-yr. ch.)	.					0.438	0.438	0.489	0.489
	.					(0.51)	(0.51)	(0.57)	(0.57)
Transition into disability, head (d)	.					0.003	0.003		
	.					(0.15)	(0.15)		
Transition into disability, spouse (d)	.					0.015	0.015		
	.					(0.80)	(0.80)		
Transition into major disability (d)	.							0.048	0.048
	.							(1.43)	(1.43)
Transition into major disability, spouse (d)	.							0.128**	0.128**
	.							(2.49)	(2.49)
Observations	.	7,404	7,404	7,404	7,404	7,404	7,404	7,404	7,404
R-squared	.	0.352	0.352	0.353	0.353	0.351	0.351	0.353	0.353
Demographic controls?	.	Y	Y	Y	Y	Y	Y	Y	Y
Mortgage controls?	.	Y	Y	Y	Y	Y	Y	Y	Y
State controls?	.	Y	Y	Y	Y	Y	Y	Y	Y
Job Loss FEs?	.	N	N	Y	Y	N	N	N	N

This table displays a set of estimation from regressions of default on LTV ratios and residual income. Default is defined as 60+ days late as of survey date (at least two missed payments). Residual Income is defined as gross family income less mortgage expenses. Column (1) repeats Column (2) from Table 5. Column (2) uses unemployment over prior year for head and spouse as IV for residual income and cumulative state HP growth as IV for the LTV ratio. Column (3) is the reduced form of Column (2). Column (4) uses involuntary job loss as of the survey date as the income IV, and Column (5) is the reduced form of Column (4). Column (6) uses general disability shocks and a 2-year Bartik instrument as the income IVs, and Column (7) is the reduced form of Column (6). Column (8) uses severe disability shocks as the income IV, and Column (9) is the reduced form of Column (8). Level of statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

continued

Table 8
Continued

B. Residual income	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative state HP growth from purchase date	.	−0.022*	.	−0.023*	.	−0.024*	.	−0.024*	.
	.	(−1.70)	.	(−1.69)	.	(−1.83)	.	(−1.80)	.
Unemployed head last year (d)	.	−0.325***	.		.		.		.
	.	(−8.76)	.		.		.		.
Unemployed spouse last year (d)	.	−0.239***	.		.		.		.
	.	(−6.44)	.		.		.		.
Involuntary unemployment, head (d)	.		.	−0.206***	.		.		.
	.		.	(−3.97)	.		.		.
Involuntary unemployment, spouse (d)	.		.	0.098	.		.		.
	.		.	(1.64)	.		.		.
Bartik instrument (2-yr. ch.)	.		.		.	10.337***	.	10.118***	.
	.		.		.	(4.61)	.	(4.50)	.
Transition into disability, head (d)	.		.		.	−0.148***	.		.
	.		.		.	(−2.83)	.		.
Transition into disability, spouse (d)	.		.		.	−0.092**	.		.
	.		.		.	(−2.17)	.		.
Transition into major disability (d)	.		.		.		.	−0.335***	.
	.		.		.		.	(−2.99)	.
Transition into major disability, spouse (d)	.		.		.		.	−0.223**	.
	.		.		.		.	(−2.45)	.
Observations	.	7,404	.	7,404	.	7,404	.	7,404	.
R-squared	.	0.335	.	0.326	.	0.321	.	0.322	.
Demographic controls?	.	Y	.	Y	.	Y	.	Y	.
Mortgage controls?	.	Y	.	Y	.	Y	.	Y	.
State controls?	.	Y	.	Y	.	Y	.	Y	.
Job loss FEs?	.	N	.	Y	.	N	.	N	.

that may link job loss propensity to default. The estimated magnitude remains negative and slightly increases (in absolute value), although the statistical significance slightly drops, as we lose some power due to the smaller number of involuntary employment spells compared to overall employment spells in the data. These estimates indicate that the effect of involuntary job loss by the head of household on the default probability is equivalent to a 36 (.055/.154) percentage point drop in equity. That the IV estimates remain quite similar when we focus on only involuntary unemployment spells and control for previous such spells assuages many of our concerns about endogeneity bias.

3.3 IV estimates based on Bartik and disability shocks

To assess the robustness of these IV results based on involuntary unemployment and prior unemployment episodes, we also construct an alternative set of instruments for residual income, which is less susceptible to endogeneity bias along some dimensions. Our alternative instrument set has two primary components, which are both motivated by previous research.

The first component in our instrument set is a disability shock that we construct based on the work of Low and Pistaferri (2015) (hereafter referred to as LP). Using PSID data, LP finds that disabilities significantly decrease the probability of working and also significantly decrease offered wages for households that choose to work.[35]

These findings imply that health disabilities result in significant declines in income. In addition, LP argues that health disabilities are exogenous shifters of employment probabilities and wages (and thus income), citing several studies to support such a position.[36]

We follow the methods of Low and Pistaferri (2015) in identifying a household in which the head or the spouse has suffered a disability, and construct dummy variables to identify a *change* in either the head's or spouse's disability status. The first set of dummy variables that we focus on indicate whether the head or the spouse has suffered any disability (moderate or severe) since the previous survey. The second set indicates whether the head or the spouse has suffered a severe disability since the previous survey.

In addition to the disability shocks, we construct an additional instrument that is meant to isolate purely *exogenous* changes in employment status that influence residual income. The instrument is Bartik-type shock based on aggregate sectoral employment flows at the national level and industry shares

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35 Specifically, LP finds that a moderate disability decreases the likelihood of working by 27 percentage points, and a severe disability decreases the probability by 74 percentage points. Conditional on working, LP finds that a moderate disability reduces wages by 6 percentage points, and a severe disability reduces wages by 18 percentage points.

36 These include (among others) Smith (2004), who found that income does not affect health status as long as one controls for education (which we do in our analysis), and Adda, Gaudecker, and Banks (2009), who found that income innovations do not affect health status.

at the state level. The idea behind the Bartik shock is that employment in all states in all industries is affected by national industry-level employment movements, but movements in a given industry have a higher impact in a state where the industry employs a greater share of the population. For example, the Bartik shock calculation for Florida would place a lower weight on national employment changes in the financial activities industries than the Bartik shock calculation for New York. In our context, the Bartik variable is a natural choice for an instrument as state-level, labor demand shocks are unlikely to be correlated with individual default decisions except through their impact on the likelihood of job loss and, in turn, income loss. The Online Appendix provides further details regarding the construction of the disability and Bartik shocks.

Column (6) in Table 7 displays the results when we instrument for income loss using the disability shock and the Bartik employment shock. The coefficient estimate is -0.109 (statistically significant at the 5% level), which is similar in magnitude to the estimates we obtained using unemployment spells in Columns (2) and (4). The first-stage results displayed in Table 8, Column (6), panel B, suggest that the disability indicators are strong predictors of income loss, which is consistent with the findings in Low and Pistaferri (2015).

IV diagnostics are displayed in the bottom two rows of Table 7. The disability and Bartik variables all exhibit strong first-stage results and easily pass weak IV tests. Since we have multiple instruments, we can also conduct over identification tests (the premise of these tests is to use each instrument one-at-a-time, and then check to see if the residuals are correlated with the excluded instrument) and in every specification, the instruments pass.[37]

In the Online Appendix, we show the results from several robustness exercises. For example, we consider the inclusion of state fixed effects in the IV specifications, we consider some alternative ways of specifying the instrumental variables (including different timing conventions for the Bartik shocks and alternative disability definitions), and we also substitute the continuous LTV variable with a dummy variable for negative equity (LTV >100). The results are consistent across these permutations. Furthermore, in the Online Appendix, we consider a similar set of IV specifications for negative income growth shocks rather than residual income and show that the results are robust.

4. Implications for Research and Policy

The foregoing analysis leads to four significant findings that we believe are relevant for both researchers and policy makers:

[37] There is, of course, no explicit way of testing the exclusion restriction. The overidentification tests come the closest and are often portrayed as tests of the exclusion restriction, but they are not direct tests because they assume that at least one of the instruments is valid.

Finding 1: *Households with low residual income default more than households with high residual income.*

Finding 2: *Most households that suffer a shock will not default.*

Finding 3: *Many households that default can afford their mortgage payments.*

Finding 4: *Very few households that can afford their mortgage payments default.*

4.1 Implications for research

Dating all the way back to Herzog and Earley (1970), researchers have studied the determinants of default using micro data. Although there is strong anecdotal evidence showing that unemployment and income shocks are important (see, e.g., Cutts and Merrill (2008)), the evidence from micro-level data does not bear this out. As Gyourko and Tracy (2014) write, "Empirical models of mortgage default typically find that the influence of unemployment is negligible." Gyourko and Tracy (2014) used simulation methods to argue that the weak relationship between income and employment and default in the data resulted from attenuation bias related to the use of aggregate (i.e., county-level and MSA-level) unemployment indicators. Finding 1 of this paper provides direct evidence of the role of household-level income shocks in the default decision, and the analysis in Section 4 shows that unemployment and disability shocks are important drivers of the income shocks that generate mortgage defaults. Thus, our results confirm those of Gyourko and Tracy (2014)[38] and also provide some support for the double trigger model of mortgage default described in Foote, Gerardi, and Willen (2008) and elsewhere.[39]

As mentioned above, the question of the importance of strategic default has occupied both researchers and policy makers. For example, Guiso, Sapienza, and Zingales (2013) conduct a survey and ask respondents, "Of the people you know who have defaulted on their mortgage, how many do you think walked away even if they could afford to pay the monthly mortgage?" Based on the answers, they conclude that in 2010, approximately 35% of defaults were strategic in nature. Finding 3 of our paper is that almost 38% of households in default could make their mortgage payments without reducing consumption. In that sense, our results confirm the importance of strategic default. However, it is important to stress again that according to Finding 4, just because strategic

[38] Indeed, consistent with previous findings in the literature, when we use aggregated unemployment instead of household-level unemployment shocks, we find a very weak connection between unemployment and default. This confirms the role of attenuation bias.

[39] Although our findings support one of the double-trigger model's main predictions that household-level cash flow shocks are an important driver of default, they are not consistent with the prediction that such shocks are a necessary condition for default. Our findings on "can pay" defaulters show that a significant fraction of defaults appear to be driven by strategic motivations.

motivations appear to play an important role among defaulters, does not mean that strategic default was extremely prevalent. Table 4 shows that even among borrowers with low equity, almost 96% of borrowers who could afford their mortgage payments continued making them. Based on these findings, an important question for researchers to ask in future surveys could be, "Of the people you know who could afford to make their monthly mortgage payment, how many do you think walked away?"

Finally, one of the great puzzles in the mortgage literature is the low frequency of defaults in the data. In standard models, default is rampant at high LTV ratios. For example, Kau, Keenan, and Kim (1993), using a contigent claims approach to modeling mortgage default and prepayment, calculate in their baseline parametrization that 100% of borrowers with LTV ratios greater than 115% will default. Yet in the typical micro-level data set, the share of borrowers who default with LTV ratios of at least 115 is in the single digits (see, e.g., Deng, Quigley, and Order 2000). The double-trigger theory proposed that once household financial stress was taken into consideration, one could reconcile the data and theory. However, the evidence is mixed. As already noted, Finding 1 shows that households with low residual income are more likely to default. Table 4 shows that "can't pay" households with low equity are 30 times more likely to default than "can pay" households with high equity. But, the actual default rate, even for this high risk group is still only 20%, or one-fifth, of the default rate generated by the model of Kau, Keenan, and Kim (1993).

The open question for research is why many borrowers who face significant hardship with few options choose to continue making their mortgage payments, while other borrowers choose not to. One possibility along these lines is that many households have a strong moral aversion to defaulting on debt, especially mortgage debt. For example, Guiso, Sapienza, and Zingales (2013) find evidence in survey data that many households consider strategic mortgage default to be an immoral practice, and as a result, are much less likely to engage in such behavior. Approximately 82% of the households in their survey report having a moral aversion to mortgage default, so it is conceivable that a large majority of our "can't pay" households hold similar reservations against default.

Another possibility is that many households have a strong attachment to their homes, and thus go to extreme measures to avoid default and foreclosure by drawing down their illiquid assets such as vehicles and retirement accounts.[40] Finally, optimistic expectations of future house prices may play an important role. The theoretical literature tells us that house price expectations are an important determinant in the decision to default.

[40] See Laufer (2012) and Schelkle (2011) for theoretical models that allow for strong attachment to homes or aversion to renting.

4.2 Implications for policy

During the foreclosure wave that swept the country before, during, and after the Great Recession, there were fierce debates among academics and policy makers about the best policies to mitigate foreclosures and prevent a future crisis. In this section we discuss how our empirical findings are relevant to this debate.

First, the signature foreclosure relief policies of the Obama Administration, the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP), focused on reducing monthly mortgage payments. Finding 1 above shows that such an emphasis was sensible. Our regression estimates from Section 3 show that residual income has economically large effects on repayment behavior and that policies that increase residual income should be effective in reducing defaults.[41]

However, Findings 2 and 3 both imply major challenges in implementing foreclosure prevention policies and illustrate, at least partly, why the policies implemented during the crisis did not achieve as much as hoped. The central goal of a HAMP modification was to reduce a households's monthly payment to an affordable level. Finding 3, however, shows that many borrowers in delinquency already have affordable payments. In Figure 1 we show this more clearly by calculating for each household in default the required mortgage payment reduction (in percentage terms) that is necessary to make the payment "affordable." We consider three definitions of affordability in the figure. The first two correspond to the definitions in Table 4: the mortgage payment is affordable if the household can maintain its consumption level from the previous year, and the payment is affordable if the household can consume the VA subsistence level, respectively. The third definition considered in Figure 1 is that the mortgage payment must satisfy the QRM "ability-to-repay" standard. The left-most column in the figure shows that the payment reduction required to achieve affordability is zero for a large fraction of households in default. In other words, many delinquent households have too much income to qualify for a loan modification. Indeed, for the two most realistic definitions of affordability, QRM and VA subsistence, more than half of the delinquent borrowers already have "affordable" mortgages. At the other extreme, the right-most column of Figure 1 shows that many delinquent borrowers (between 15% and 40% depending on the affordability definition) require a 100% reduction (or more) in their monthly payment to achieve affordability. Complete payment reductions obviously present a problem for loss mitigation policies since the logic behind them is that the lender will recover more than through a foreclosure. Obviously, this would not hold if the borrower pays nothing. Figure 1 shows that the inframarginal borrowers are skewed toward small payment reductions which, according to

[41] Other previous research, including Fuster and Willen (2012) and Hsu et al. (2014), makes a similar point.

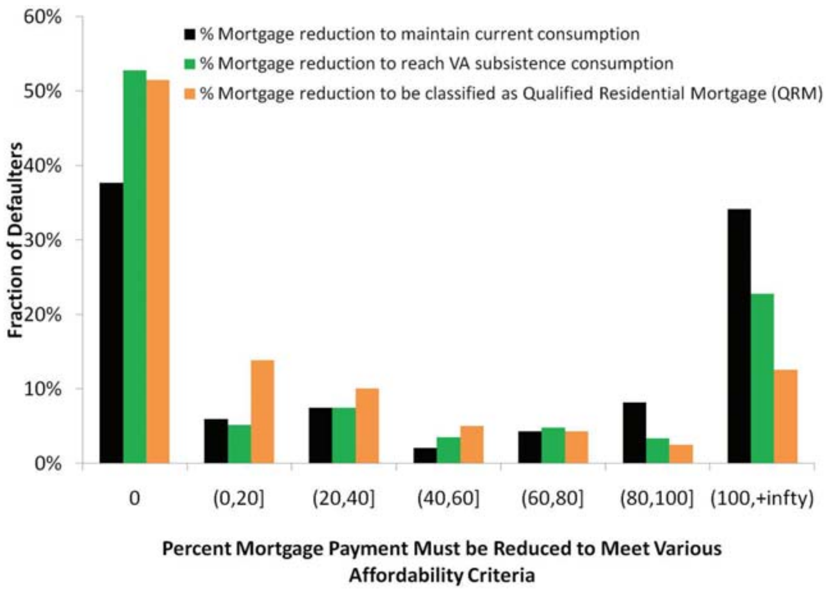

Figure 1
Mortgage affordability measures among defaulters
Sample includes 60+ days late defaulters from the PSID main sample for 2009–2013. Percentage reduction calculated using 1st and 2nd mortgage. Payment reduction calculated as $min((m_{max} - m)/m, 0)$, where m_{max} is the maximum payment a household can make and still have (1) the same consumption, (2) VA residual consumption, and (3) meet the definition of QRM. VA residual income defined in the text. QRM defined using 43% DTI after adjusting for insurance, taxes, other debt obligations, and alimony payments.

our regression estimates, would only have small effects on their likelihood of repayment.

One idea that has been popular during and since the foreclosure crisis is to preemptively offer loan modifications to borrowers who are at increased risk of default. The logic is that such modifications are "win-win" because in addition to the obvious benefit to the borrower, the lender gains as the expected cost of reduced payments is believed to be less than the expected losses from foreclosures. Finding 2 illustrates why preemptive payment reductions were never popular with lenders, even when applied to borrowers at elevated risk of default. If we look at Table 4, we can find a group of borrowers with highly elevated default probabilities: "Can't pay" borrowers with high LTV ratios are approximately 30 times more likely to default than "can pay" borrowers with low LTVs ratios. Finding 2, however, is that 80% of these high risk borrowers do not default. Thus, a loss mitigation plan that targeted only these high risk borrowers, would see 80 cents of every dollar of payment reduction go to a household that likely would have made its mortgage payment anyway. In addition, according to the table, if payment reduction takes the residual income of "can't pay" borrowers above the VA subsistence level (i.e., Column (2)), the default rate is approximately 9.5%. In other words, if lenders give payment reductions to 100 borrowers, for 80 it is basically a windfall as they likely would not have defaulted in the absence of the reduction, and only ten defaults would actually be prevented. This suggests that the cost of a foreclosure must be 8 times greater than the payment reduction to make it profitable to the lender.

Finally, at the peak of the crisis, some commentators felt that policy makers needed to respond to the problem of strategic default. Finding 3 shows that many defaulters could make their mortgage payments but Finding 4 shows that at no point did it reach the epidemic proportions that some feared: the overwhelming majority of borrowers who could make their mortgage payments did make them as did many of those who, as far as we can tell, could not afford their payments.

5. Conclusion

To design efficient foreclosure mitigation policies, it is necessary to understand the sources of mortgage default. While there is broad agreement that a number of factors, including housing equity, employment, and liquidity, may potentially contribute to default because of data limitations, it has been impossible to directly test the relative importance of these factors. Using new PSID data that includes detailed information on mortgagors' budget constraints, such as income and employment status, consumption expenditures, and assets, we measure the importance of ability to pay for the mortgage default decision and assessed the significance of strategic default.

In our empirical analysis, we find a significant role for both factors. Among households in default, strategic motives appear to play an important role, as approximately 38% of households in default appear to have the ability to pay their mortgage without reducing their consumption below their predefault levels. Furthermore, using an instrumental variables design, we find that housing equity is an important predictor of mortgage default, holding residual income constant, which is also consistent with strategic motives playing an important role. At the same time, we find an important role played by household-level income shocks including unemployment and disability shocks. Our IV estimates indicate that a 10% decline in residual income raises the probability of default by between 1.1 and 2.5 percentage points, depending on the particular instrument set.

An additional contribution of this paper is to show the reluctance of most mortgage borrowers, even those who are experiencing significant financial distress, to default on their loans. We show that approximately 80% of households that need to cut their consumption to subsistence levels in order to make their mortgage payments ("can't pay" borrowers) continue to make their mortgage payments. Furthermore, we find that nearly 96% of low equity borrowers with the ability to pay remain current on their loans. These findings provide a simple explanation for why lenders rarely preemptively renegotiate with borrowers who have extremely limited resources to pay their mortgage, since the majority of these borrowers will continue to pay.

The PSID data have allowed us to analyze strategic default and the importance of income shocks for the mortgage default decision in more detail than prior studies in the literature, but a significant amount of work remains. We leave it to future researchers to develop higher-frequency asset, mortgage default, and consumption data sets, which will ultimately allow the profession to better understand default behavior.

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