Household Savings and Mortgage Default*

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Abstract

This paper studies the effect of the household's lack of liquid assets on mortgage default. Using administrative data from banking and credit card transactions, I find that a significant number of households lack liquid assets, and that these households are more likely to default on their mortgages. The effect of the lack of liquid assets on mortgage default is amplified during unemployment. When comparing liquid assets with income, I find that high income households that lack liquid assets are more likely to default on their mortgages compared to low-income households that have more savings. Finally, households that lack liquid assets reduce consumption dramatically during the period in which they default on their mortgages. These findings have implications for mortgage default theory and consumption theory.

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1 Introduction

A fundamental issue in household finance concerns the factors that lead individuals to default on their loans. The largest loan for most households is their mortgage, and mortgage defaults have had a huge impact on the economy, illustrated most vividly through the 2008 financial crisis. Yet, little is known about the factors that lead households to default. Are mortgage defaults merely a reflection of households income shocks, or do they reflect something more fundamental about households financial acumen and habits? How does a households financial fragility, reflected by low savings and being prone to overdraft fees, affect the likelihood of defaulting on its mortgage? This paper addresses this question using a unique database on household financial behavior.

A large number of households lack liquid assets. For example, Lusardi, Schneider, and Tufano (2011) surveyed 1,931 households and found that nearly half of the respondents could not come up with \$2,000 in a month. Using data from the Panel Study of Income Dynamics (PSID), Caner and Wolff (2004) find that over 46 percent of households had less than \$5,000 in liquid assets. Another survey by the Federal Reserve Bank found that 47 percent of respondents could not come up with \$400 without selling possessions or borrowing money.[1] More surprising is the degree to which even high-income households also lack liquid savings. Lusardi et al. (2011) find that 23% of households with incomes between \$100,000 and \$150,000 reported that they could not come up with \$2,000 in a month, with similar results found in the survey by the Federal Reserve.

Assuming that these households with low savings are financially constrained, they are vulnerable to financial disruption such as income shocks, divorce, or emergency expenses. When these households face such shocks, they may have no other option than to forcibly adjust their consumption, in part by reducing housing expenditures.

[1]See https://www.federalreserve.gov/econresdata/2014-report-economic-well-being-us-households-201505.pdf.

In this paper, I empirically examine the importance of the lack of liquid assets on mortgage default, with an emphasis on exploiting unemployment shocks to highlight the effects of ex-ante financial fragility. To my knowledge, this study is the first to examine the household's savings in liquid assets and unemployment simultaneously. To do this, I employ a unique administrative dataset that includes detailed bank and credit card information at the transaction level for 2.7 million households from July 2010 to May 2015. Using this dataset, I find that a substantial number of households lack liquid assets. I consider households to lack liquid assets if they are in the low tercile in interest earned and if they have incurred overdraft fees. I measure unemployment shocks by the receipt of unemployment benefits.

I find that the households that incurred overdraft fees were 43 percent more likely to default on their mortgages, compared to households that did not incur overdraft fees. Similarly, I find that households in the lowest tercile of savings were also 43 percent more likely to default on their mortgages. On the other hand, households that participated in the financial markets through transacting on their brokerage accounts were 22 percent less likely to default. Compared to these measures of liquid assets, other household characteristics had smaller effects on mortgage default. Households in the lowest income tercile were only 22 percent more likely to default on their mortgages compared to households in the middle and high income terciles, and households that had a high ratio of spending relative to their income were only 8 percent more likely to default. Households that had a high mortgage-payment-to-income (MTI) ratio were 14 percent more likely to default. The economic magnitude of the effect of the lack of liquid assets on mortgage default, 43 percent, is much larger that of low income, 22 percent.

Financially fragile households that become unemployed are much more likely to default on their mortgages compared to non-fragile households that become unemployed. Households that had incurred overdraft fees were 160 percent more likely to default when they subsequently became unemployed. In contrast, households that had not incurred overdraft fees that subsequently became unemployed were only 50 percent more likely to default on their mortgages in the months in which they were unemployed. Households who were in the lowest tercile of interest earned that subsequently became unemployed were 97 percent more likely to default compared to the months in which households continued to be employed. However, households that were in the high tercile of interest earned who subsequently became unemployed were only 23 percent more likely to default in the months in which they became unemployed. The large contrast between fragile households (i.e. incurred overdraft fees or were in the lowest interest earned tercile) and households had more in liquid assets (i.e. did not incur overdraft fees or were in the highest interest earned tercile) highlight the importance of liquid assets as a significant determinant of mortgage default.

Next, I compare liquid assets and income as determinants of mortgage default. It is not just the poor who lack liquid assets. I find that 15 percent of households in the highest income tercile incurred overdraft fees and that 18 percent of households in the highest income tercile belong in the lowest interest earned tercile, consistent with the findings in the surveys above.

Households that incurred overdraft fees were more likely to default on their mortgages, regardless of whether they belonged in the low, mid, or high income tercile. High income households that incurred overdraft fees were 20 percent more likely to default on their mortgage, compared to households in the middle income tercile that did not incur overdraft fees. Similarly, high income households that were in the low interest earned tercile were 17 percent more likely to default on their mortgages compared to households in the middle income and middle interest earned tercile.

Finally, I examine consumption and debt repayment surrounding mortgage default. I find that households that lacked liquid assets reduced their consumption dramatically leading up to the time of default. Households that had more liquid assets also reduced their consumption, but not to the same extent. In addition, I find evidence of households paying back their credit card debt as they default on their mortgages This is consistent with the finding of Cohen-Cole and Morse (2010) and Chan, Haughwout, Hayashi, and van der Klaauw (2015), who find that consumers decide to preserve access to credit card borrowing as they default on their mortgages.

Theory provides two main spectrums of predictions on the effect of fragility on mortgage default. In a world without financial constraints, mortgage default does not depend on household fragility. Instead, households make default decisions based on an option-theoretical framework, where the household exercises its default option when the cost of the mortgage exceeds the value of the default option. In this setting, households default only when they have negative home equity (Kau, Keenan, and Kim 1994, Vandell 1995, Deng, Quigley, and Van Order 2000).

In an alternative class of models that incorporate financial constraints, mortgage default is determined by a double trigger mechanism. In these models, negative home equity is a necessary, but not sufficient condition for default. Default is determined by borrowing constraints as well as income shocks such as unemployment and medical emergencies (Gerardi, Shapiro, and Willen 2007, Bajari, Chu, and Park 2011, Campbell and Cocco 2015, Schelkle 2015). Households that are fragile are much more likely to encounter these borrowing constraints, and hence these models predict that financially fragile households will be more likely to default on their mortgages.

Other theories on household behavior explain why households are fragile. A particular strand of consumption theory suggests that fragility may even be preferred. The lack of liquid savings could be a self-commitment device (Laibson (1997)) or simply an optimal portfolio allocation (Kaplan and Violante (2014) and Kaplan, Violante, and Weidner (2014)). Regardless of the rationale, financial fragility exposes the household to financial disruption.

Despite the emphasis on fragility in the theoretical literature, the empirical literature on mortgage default has mostly been focused on negative equity, primarily due to data constraints.[2] Data on household-level fragility or unemployment had been largely unavailable to researchers until recently. Notable exceptions are Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010) and Gerardi, Herkenhoff, Ohanian, and Willen (2015), who employ new datasets on household level credit card utilization and unemployment, respectively.

Continuing this trend of using novel datasets, this paper contributes to the empirical literature on household behavior by testing the theoretical predictions about household savings and mortgage default. More importantly, by identifying an important link between liquid assets and mortgage default, this paper sheds light on what has been at the center of economic policy debates over the recent decade.

2 Data and Empirical Methodology

2.1 Data

A key contribution of this paper is the data. Prior researchers have mostly relied on loan-level data to examine why households default on their mortgages. This loan-level data, often collected from mortgage servicers, is rich in information about loan performance and loan origination. For example, in the Freddie Mac Single Family Loan-Level Dataset, data on loan-to-value (LTV), debt-to-income (DTI), credit scores, and interest rates are provided at origination and unpaid principal balance (UPB) and delinquencies are kept track of as part of the monthly performance dataset.

If households make default decisions solely based on the option value of the mortgage,

[2] The large empirical literature on mortgage default include Vandell (1978), Campbell and Dietrich (1983), Quercia and Stegman (1992), Vandell(1995), Deng, Quigley, and Van Order (2000), Clapp, Deng, and An (2006), Gerardi, Shapiro, and Willen (2007), Amromin and Paulson (2009), Foote, Gerardi, Goette, and Willen (2009), Mayer, Pence, and Sherlund (2009), Mian and Sufi (2009), Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010), Goodman, Ashworth, Landy, and Yin (2010), Bajari, Chu, and Park (2011), Demyanyk and Van Hemert (2011), Fuster and Willen (2013), Palmer (2015), Ferreira and Gyourko (2015), and Gerardi, Herkenhoff, Ohanian, and Willen (2015) among others.

as in the option theoretic models, then the loan-level data would be sufficient in explaining why households default on their mortgages. However, if other factors such as household savings, unemployment, health shocks are also considered by households when they are making the decision on whether to default on their mortgage, we need to know how much savings the household has, whether they are unemployed, and if they face large medical bills. Unfortunately, information on these household events are unavailable in loan-level datasets.

In this paper, I attempt to advance the literature by using data that contains bank and credit card transactions from 2.7 million households to look at how savings, income, unemployment, and other characteristics affect the households default decision. The data is from an online website that aggregates bank and credit card accounts for households. Households use this aggregation service as a convenient way to keep track of their savings and spending, by providing the website of usernames and passwords of different financial institutions so that the website can gather this information and present the information in a single page.

This transaction-level data has become available to researchers in recent years. Examples of recent studies using this type of banking and credit card transaction data include Baker (2015), Baugh (2015), Baugh, Ben-David, and Park (2015), Baugh, Ben-David, Park, and Parker (2014), Bernstein (2016), and Kuchler (2015). These papers, with the exception of Bernstein (2016), are focused on testing consumption theory, since this type of data is naturally rich in detail on consumer spending. Bernstein (2016) looks at the effect of negative equity of mortgages on labor supply.

The data includes the date, description, amount, and other variables for each transaction. I use keyword searches to identify mortgage, income, unemployment benefits, overdrafts, interest earned, brokerage, and consumption transaction. After each transaction is classified, it is summed up at the monthly level. For credit card repayment, I add all the credit transactions for the month as repayment, and add all the debit transactions for the month as borrowing. Then I lag the sum of debit transactions so that it is matched with the sum of credit transactions one month later. This is done to match the payment cycle of credit cards. The difference between the two amounts is the amount that the household has repaid or borrowed from the credit card company.

Since unemployment benefits are administered at the state level, benefits for each state are identified separately. For example, unemployment benefits for New York often come with the description nys dol ui and unemployment benefits for Texas often come with twc benefit ui. nys dol stands for New York State Department of Labor and twc stands for the Texas Workforce Commission. Using this method, I identify 27 states, which are Alaska, Arkansas, Colorado, Connecticut, Delaware, Florida, Georgia, Iowa, Idaho, Louisiana, Massachusetts, Maine, Michigan, Minnesota, Missouri, North Carolina, New Mexico, New York, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Washington, West Virginia, and Wyoming. States such as California are missing because they issue unemployment benefits to a separate debit card that is not captured in the data. In other states such as Ohio, unemployment benefits are hard to identify using transaction descriptions since it is paid by the the Department of Job and Family Services, and do not distinguish between unemployment benefits and other welfare programs.

Mortgages are selected based on mortgage-related keywords such as "mtg", "mortgage", "home loan" or debit transactions to major mortgage servicers such as "ocwen" and "dovenmuehle". Income is identified by searching for keywords such as "payroll", "salary", or "direct deposit". Overdraft fees are identified by keywords such as "overdraft fee" or "nsf returned item fee", retail consumption by keywords for major retailers such as "wal mart", "target", or "costco", grocery consumption by keywords such as "kroger" and "safeway", restaurant consumption by keywords such as "mcdonalds", "burger", "pizza", brokerage transactions by keywords for large brokerages and mutual fund companies and so forth.

While these variables are directly observed, some other variables must be inferred. The most important of these is the indicator for whether the household has defaulted on its mortgage. I consider a household to have defaulted on its mortgage if the household has missed more than three mortgage payments. However, while I can observe mortgage payments, the termination or suspension of these payments does not always mean that the household has defaulted on its mortgage. It is possible that the household has fully paid off its mortgage, sold off the house, or started paying the mortgage from a different account.

In order to correctly identify mortgage default, I impose a number of filters in the data. First, I require that all the households in the sample to have not received social security payments at any time during the sample period. This is because households that receive social security payments are more likely to be old enough to have fully paid off their mortgages. Households that received social security payments were dropped from the sample.

Next, I identify households that have larger average mortgage payments in the last 3 months than compared to the previous 12 months. I consider these households to have fully paid off its mortgage or to have sold the house when they stop paying their mortgages. Similarly, I identify households that have larger average monthly sums of transactions larger than $5,000 in the final 6 months than compared to the previous 12 months. I also treat these households to have fully paid off its mortgage or to have sold the house when they stop paying their mortgages.

Finally, I look at additional ways of identifying default instead of solely relying on whether the household has stopped paying its mortgage. The first of these additional methods is to look at cured mortgages. I find mortgages that households have started paying off again, after more than 3 months of suspending the payment of mortgages. I also look at households that have reduced their consumption by more than 30 percent and households that experience income shocks. The results for these alternative definitions are not reported in this paper, but the results are consistent regardless of the definition of mortgage default.

Another drawback is that data lacks information on loan balances. Therefore, instead of using the loan-to-value ratios directly, I control for the changes in loan-to-value by using the changes in the real estate prices in the households city of residence. The city of residence is the most common city within a state in which a household makes its transactions. Then I take the Zillow Home Value Index from Zillow.com and match it to each household. Since I do not have loan balance data, I cannot see if the household has negative equity on its home. I also employ region-time fixed effects in some regressions to control for the changes in the house prices in the region as well as other economic factors such as regional unemployment.

The data in this paper complements prior research on the determinants of mortgage default. This paper can reliably observe household income, unemployment, savings, and consumption, but must estimate whether the household has defaulted on its mortgage, and tries to control for other variables such as LTV. In contrast, prior papers in general can observe delinquency, LTV, and credit scores but did not have access to household savings, unemployment, and consumption. Since theory predicts that unemployment is an important predictor of default, many studies use regional unemployment as a proxy for individual unemployment. This attenuates the actual effect of unemployment, leading to conclusions that unemployment is not as important as other variables that were directly observable such as negative equity (Elul et al. (2010), Goodman et al. (2010), Gyourko and Tracy (2014)). The data on savings is even less accessible.

Despite the restrictions in the data, there are two studies that analyze the effect of liquidity constraints and unemployment on mortgage default. Gerardi et al. (2015) use a supplement to the PSID, which combines the households mortgage data with information on employment, income and other characteristics and find that unemployment is an important predictor of default. Elul et al. (2010) combine mortgage servicer data with household credit card information from Equifax using balance, date, and zip code to measure household liquidity and find that liquidity as defined by credit card utilization was as important as negative equity in predicting default.

There are differences between the data used in this paper and the PSID or Equifax data used in Gerardi et al. (2015) and Elul et al. (2010). First, the PSID surveys used in Gerardi et al. (2015) are cross-sectional in nature. For example, it has information on savings but it is recorded at the time of the survey along with other variables such as mortgage default. Therefore it is not possible to find the effect of savings prior to a shock that would lead the household to default on its mortgage. Additionally, there is a difference in sample size. The final sample used by Gerardi et al. (2015) has 5,281 households, compared to the 265,144 households in the final sample of this paper. The Equifax data used by Elul et al. (2010) does not have information on unemployment and savings. However, the PSID and Equifax also have their advantages. The PSID is rich in demographic information such as race and age, and also has better data regarding LTV and default. The Equifax data has information on credit card limits and it is possible to link it to loan-level data which has very accurate information on default.

In the discussion on the importance of middle-income, high-income, and prime borrowers on the financial crisis of 2008, Mian and Sufi (2015) point out that income may have been overstated during the housing boom of the mid-2000s due to mortgage fraud. Though not covering the same period, I can directly observe income receipt and provide additional evidence on the determinants of mortgage default for the middle class.

The raw data contains transactions for 2.7 million households from July 2010 to April 2015. Of the 2.7 million, I restrict the data to the 792,786 households that have both mortgages and income transactions. Next, I restrict the data to the households that live in the 27 states in which unemployment benefits can be identified. Households are considered to be living in a particular state if more than two-thirds of the transactions that have location information are in that one state. After this restriction, the sample is reduced to 430,024 households. Finally, I require that households receive no social security payments at any time in the data and that there be six consecutive months of both income receipt and mortgage payment. This is done so that the households in the final sample are those that are likely to have their main bank accounts registered with the online aggregator. This six month period is where I observe the households financial conditions prior to the default period. This leaves a final sample of 265,144 households.

The final sample of 265,144 households is not a representative sample of the US population. The households in the data select into the sample by choosing the services of the online aggregator. This may mean that the data includes households that are more technologically advanced, higher educated, younger, and also have more interest in managing their finances compared to the rest of the population. This is reflected to some degree in the geographic distribution of households in the sample. Figure 1 shows the distribution of households in each state, compared to the 2010 United States Census. Panel A shows the proportion of households residing each state and Panel B shows the percentage point difference between the final sample of households used in this data and the 2010 Census. Households in this sample are particularly heavily concentrated in New York and to a lesser extent in Texas. Households are also over-represented in Florida, Georgia, and Connecticut. In contrast, households are heavily under-represented in Pennsylvania and Michigan.

Table 1 presents the summary statistics. Out of the 265,144 households in the sample period, 28,082 households experienced default. Fifty percent of households received $0.36 or less in monthly bank interest during the 6 month pre-period. Assuming a five basis-point interest rate, this equates to savings of around $8,640 in the bank savings account, which is higher than the survey results from the Federal Reserve Bank that showed 47 percent of the respondents could not come up with $400 without selling possessions or borrowing money. Eighty three percent of households did not have any transactions with brokerages in the pre-period, though when averaged, had $547 in brokerage transactions. Nineteen percent of households had incurred overdraft fees, which average to $3 for the whole sample. Retail consumption was$413, restaurant consumption $148, and grocery consumption $115 on average for the sample.

In Table 2, I look at the household's liquid assets in more detail. In Panel A, I find that a third of the households had less than \$0.103 in monthly interest earned per month, which tranlates into \$2,472 in bank balance when assuming a five basis-point interest rate. Even for households in the high income tercile, 18 percent of houseoholds had less than \$2,472 of cash in the bank. In Panel B, I find similar results. 19 percent of households had incurred overdraft fees in the 6 month pre-period and around 15 percent of households in the high income tercile had incurred overdraft fees. These results are consistent with the surveys that find that over 20 percent high income households have trouble in coming up with \$2,000 in 30 days and not having \$400 to cover emergency expenses.

2.2 Empirical Methodology

The main analysis consists of a dynamic logit model for default that is equivalent to discrete hazard models (Shumway (1998)). The dependent variable is mortgage default which is defined to be households that have missed more than three mortgage payments. Observations before the end of the pre-period and observations that follow delinquency are dropped from the sample. For example, if a household had a pre-period from Jan 2011 to June 2011 and became delinquent in May 2012, then the main sample would start from June 2011 and end in May 2012. The dependent variable would equal zero for all months except May 2012, which would equal one.

In the pre-period, I divide the sample into terciles based on savings, income, spending, and mortgage-payment-to-income (MTI) ratios. Savings consists of three dummies based on how much interest the household had earned in the pre-period. If the household belongs in the tercile with the lowest interest earned, it would equal one for the low savings dummy and zero for the mid savings and high savings dummies. The similar procedure is applied to income and spending. Spending is defined as the monthly average of the ratio between consumption and income in the pre-period.

Stock ownership and overdrafts are dummies that equal one if the household had brokerage transactions and overdraft fees in the pre-period, respectively. The Zillow Index represents that change in real estate prices in the city in which the household resides. I also include state and year-month fixed effects and cluster the standard errors by household. Following Gross and Souleles (2002) and Elul et al. (2010), I include a fifth order polynomial in account age to allow the hazard function to vary nonparametrically. The logit regression results are presented as relative risk unless specified otherwise.

When comparing the effect of income and savings on the likelihood of mortgage default, I use categorical indicator variables instead of interaction terms. This is due to the difference in the interpretation of the interaction in logit regressions (Ai and Norton 2003). For example, when I estimate the effect of high-income of mortgage default, the logit regressions estimate the log-odds of mortgage default for the high-income households. The logit regressions estimates an interaction between income and savings as the interaction between the log-odds of each variable, and thus the coefficient on the interaction is multiplicative instead of additive, as it is for linear regressions. For example, if the likelihood of default for high-income households goes from 1 percent to 10 percent when becoming unemployed and the likelihood of default for low-income households goes from 20 percent to 80 percent, the logit regression would consider the increase in default likelihood for high-income households to be more important since it is a 10-fold increase, whereas the default likelihood for low-income households is less important since it is a 8-fold increase. While the multiplicative interpretation can be useful in some applications, I use categorical dummies to avoid these problems.

3 Results

In this paper, I present three primary results. First, I find that the lack liquid assets is an important determinant of mortgage default. The effect of liquid assets on mortgage default is stronger when the household becomes unemployed, as households that lack liquid assets are more fragile, thus vulnerable to shocks. These results are consistent with the double trigger models of mortgage default.

Second, I find that the lack of liquid assets is a more important predictor of mortgage default than income. Households that lack liquid savings that have high income are more likely to default on their mortgages than households with more liquid assets that have low income. This finding is broadly consistent with the existence of the wealthy hand-to-mouth documented by Kaplan and Violante (2014) and Kaplan, Violante, and Weidner (2014).

Third, I find that the decline in consumption surrounding mortgage default is large for households that lack liquid assets. These households dramatically decrease their consumption leading up to mortgage default, but maintains consumption after delinquency. Compared to households that lack savings in liquid assets, the decline in consumption for households with higher savings in liquid assets is more gradual. These results are consistent with the financial constraints literature in consumption theory (Hayashi 1985, Zeldes 1989).

I also look at credit card debt repayment surrounding mortgage default. I find that households that lacked liquid assets tended to repay their credit card debt, perhaps in an attempt to preserve their access to financing. This repayment of credit card debt is not as clearly prevalent for households with savings in liquid assets. Chan et al. (2015) show similar results, where they find that households defaulted on their mortgages whiles prioritizing the repayment of credit card debt and auto loans. The results for consumption and credit card debt also shines some light into the pecking order of coping methods proposed by Lusardi et al. (2011).

3.1 Household Savinsg and Mortgage Default

In Table 3, I look at the measures of household savings in liquid assets and examine how they are related to mortgage default. In column (1), I find that households than incurred overdraft fees in the pre-period were 43 percent more likely to default on their mortgages compared to households that did not incur overdraft fees.

If overdraft fees are generally related to the poor, financial market participation is about the rich. For most households, the largest asset class is usually their house and not the stocks (Campbell and Cocco 2003). In column (2), I look at households that had participated in the financial markets through brokerage transactions and find that these households were 22 percent less likely to default on their mortgages.

In columns (3) and (4), I look at the interest earned terciles and their relationship to mortgage default. In column (3), I find that households in the low interest earned tercile were 43 percent more likely to default on their mortgages. In column (4), I find that households in the middle interest earned tercile were 26 percent less likely to default on their mortgages than households in the low interest earned tercile. Households in the high interest earned tercile were 34 percent less likely to default on their mortgages, compared to the low savings tercile.

In columns (5), I put the overdraft, brokerage, and low savings dummies in single regressions for comparison. I find that the magnitude of the effect of overdrafts and low savings on mortgage default does not decrease by much, and the effect for financial market participation through brokerages only decreased by around 2 percentage points.

In Table 4, I look at other household characteristics such as income, spending, and mortgage-to-income and examine how they are related to mortgage default. In columns (1) and (2), I look at the income terciles and their relationship to mortgage default. In column (1), I find that households in the low income tercile were 24 percent more likely to default on their mortgages. In column (2), I find that households in the middle income tercile were 17 percent less likely to default compared to households in the low income tercile. Households in the high income tercile were 22 percent less likely to default compared to the low income tercile.

In column (3) I find that households in the high spending tercile in the pre-period were 3 percent more likely to default compared to households that were not in the high spending tercile. In column (4), I find that households in the high mortgage-to-income ratio tercile were 12 percent more likely to default compared to households that were not in the high mortgage-to-income ratio tercile.

In columns (5), the variables in Table 2 and Table 3 are put into a single regression. The variables related to fragility are not much different from their coefficients in Table 2. However, the magnitudes for other household characteristics were decreased significantly in the multivariate regression. For example, the the low income tercile are now only 14 percent more likely to become delinquent when controlling for other variables, and other variables such as mortgage-to-income drops to 3 percent. Table 2 and Table 3 show that the measures for household savings in liquid assets tend to be more important as determinants of mortgage default than household characteristics such as income, spending, or leverage.

In Table 5, I look at the vulnerability of financially fragile households to shocks by explicitly looking at unemployment shocks and look that how it affects mortgage delinquency. In column (1), I find that households that incurred overdraft fees in the pre-period were 160 percent more likely to become delinquent on their mortgages when they became unemployed, compared to the months in which households in the sample were employed. Households that did not incur overdraft fees in the pre-period were only 50 percent more likely to become delinquent on their mortgages when unemployed, compared to the months in which households were employed.

In column (2), I find that households that had brokerage transaction in the pre-period were only 26 percent more likely to default in the months in which those households become unemployed compared to the months where the households remained employed. the 26 percent increase in likelihood of default is also insignificant at the 5 percent level. Households that did not have brokerage transactions and became unemployed were 82 percent more likely to default in the months in which those households were unemployed.

In column (3), I find that households in the low tercile of interest earned in the pre-period that became unemployed were 97 percent more likely to default on their mortgages compared to the months in which households were still employed. For households that were in the middle tercile of interest earned, the likelihood of defaulting on its mortgage went up by 96 percent when they became unemployed. Households that were in the high savings tercile were 23 percent more likely to default in the months where the households became unemployed.

In Table 6, I perform a similar type of analysis as with Table 5, but using income, spending, and mortgage-to-income terciles. In contrast to Table 5, I find that spread between the extreme terciles to be smaller. High income households that become unemployed are 59 percent more likely to default in those months, compared to the months in which households stay employed. Low income households that become unemployed are 81 percent more likely to be delinquent than employed households. The difference between the two terciles are only 22 percentage points. Similarly, the difference between high spending households and low spending households are only 42 percentage points and the difference between high MTI households and low MTI households is only 1 percentage point. These are small compared to the 110 percentage point difference between overdraft households and non-overdraft households and the 74 percentage point difference between low savings households and high savings households.

In this section, I find that overdraft fees and savings, as measures of household savings in liquid assets, were significantly associated with mortgage default. When these variables were interacted with unemployment shocks, it implied a significantly higher risk of default.

These results strongly support the double-trigger models of mortgage default.

In untabulated results, I find that the effect of unemployment alone on mortgage delinquency to be large. Previous research typically found small effects for unemployment (Elul et al. 2010, Goodman et al. 2010), due to measurement issues (Gyourko and Tracy 2014). Households that become unemployed were 82 percent more likely to default than households that remained employed. These large results are consistent with the findings of Gerardi et al. (2015), who also utilize individual-level data.

3.2 Household Savings versus High Income

Next, in Table 7, I look at how the effect of the household financial fragility on mortgage delinquency varies with income level. In Column (1), I find that households that incurred overdraft expenses, regardless of whether the household is in the high, middle, or low income tercile, had higher likelihoods of being delinquent than households that did not incur overdraft fees.

In columns (2) and (3), I interact spending and mortgage-to-income instead of income and find results that emphasize the importance of liquid assets. However since income levels are generally more meaningful in describing household outcomes than spending habits or leverage, I focus the analysis on income.

In Table 8, column (1), I look at how the effect of savings on mortgage delinquency varies with income level. The results are similar to the ones in Table 6. When households were in the low savings tercile, they were more likely to be delinquent whether or not they were in the high income tercile. The high income but low savings households were 17 percent more likely to be delinquent compared to middle income and middle savings households.

In table 8, I control for employment and find similar results. Compared to an omitted category of middle income, non-overdraft, and employed households, the low income, non-overdraft, and employed households were 16 percent more likely to default. When looking at the employed households that are high income but have overdraft fees, the increased likelihood of default is 20 percent.

These findings also support the work by Kaplan and Violante (2014) on the wealthy hand-to-mouth, households that are wealthy on paper but have their investment in illiquid assets and have high consumption sensitivity to income. I find many households in my sample are wealthy in the sense that they are homeowners, and who are hand-to-mouth in the sense that they are liquidity constrained (i.e. incurring overdraft fees) These wealthy hand-to-mouth households have a high propensity to become delinquent on their mortgages.

These results are also relevant to the discussion on the causes of the financial crsis. When we think of the causes of the financial crisis of 2008, we often visualize Wall Street bankers and mortgage brokers that lent money to subprime borrowers who bought houses that they could not afford. In particular, Mian and Sufi (2009) provide evidence that the expansion of mortgage credit to subprime borrowers was closely linked to the mortgage defaults during the crisis.

However, recent research shows that high-income, middle-income, and prime borrowers may have played a larger role in the 2008 financial crisis than previously realized. Adelino, Schoar, and Severino (2015, 2016) find that mortgage originations increased for all income levels and FICO scores in the pre-2007 period. They also find that middle-income, high-income, and prime borrowers sharply increased their share of delinquencies during the crisis. Also, Ferreira and Gyourko (2015) find that about twice as many prime borrowers lost their homes compared to subprime borrowers during 2006 to 2012. Figure 1 uses data from HOPE NOW, an organization that helps homeowners pay their mortgages, to show the trend in foreclosures for prime and subprime mortgages during the crisis. The number of prime borrowers that lost their homes is much larger than the number of subprime borrowers that lost their homes. This is consistent with the findings of Adelino, Schoar, and Severino (2015, 2016) and Ferreira and Gyourko (2015). The importance of liquid assets as a determinant of mortgage default for high income households, combiend with the finding that many high income household do not have much in liquid assets, show why high income households may have defaulted in large numbers during the financial crsis.

3.3 Consumption and Credit Card Debt Surrounding Mortgage Delinquency

Finally, I look at consumption and debt repayment surrounding mortgage default. Adverse shocks that accompany mortgage delinquency are not easy for households to deal with. If the household has sufficient savings then it can try to smooth the impact of the shock. However, if the household lacks savings, then they must respond to shocks in other ways, one of which is to reduce consumption.

In Figure 3, I show the trend in retail consumption surrounding mortgage default. Households that incurred overdraft expenses decreased their consumption by $98 at delinquency, which is a significant amount (27%) compared to the mean spending on retail of $369 by defaulting households. After default, the decline in consumption tended to stablize, though the household eventually decreases their consumption again later on. For non-overdraft households, the effect is not as large, but these households still reduce their consumption. The reduction is more gradual compared to overdraft households, but their consumption also decreases as time goes by.

In Figures 5 and 6, similar reduction of 20 to 30 percent can be found for restaurant and grocery spending. The difference in the reduction in consumption between fragile and non-fragile households are narrower for grocery consumption, due to it being less of a discretionary good, and also due to the opportunities of home production (Aguiar and Hurst 2005).

In Table 10, I look at credit card debt repayment surrounding mortgage delinquency. I find that households tend to repay their credit card debt during the same time that they dramatically reduce consumption and default on their mortgages. This result is also confirmed by Chan et al. (2015). This gives implications on the importance that households put on the availability of consumer credit.

These results shed some light in to the pecking order of coping methods proposed by Lusari et al. (2011). I find that households initially reduce their consumption when hit by an adverse shock, which is followed by mortgage default. The suspension of mortgage payment gives some relief to the households in terms of stablized consumption. Despite the willingness to use credit to cope with shocks in Lusardi et al. (2011)'s survey, I fine that households, on the contrary, pay back their credit card debt.

4 Conclusion

In this paper, I use administrative data from banking and credit card transactions to obtain data on ex-ante household savings in liquid assets and unemployment. Using this data, I find that households that lack liquid assets are more likely to default on their mortgages. They are also more sensitive to unemployment shocks compared to households with more savings in liquid assets. These finding are in support of the double-trigger hypothesis in mortgage default theory.

I also compare household savings in liquid assets and income and find that household savings is a more significant predictor of mortgage default than income. High income households that lack liquid savings are more likely to become delinquent on their mortgages than low income households that have more in liquid assets. These findings are broadly consistent with the research on the wealthy hand-to-mouth, where high income households may find it optimal to put themselves into a liquidity constrained position to gain higher returns on illiquid assets such as housing.

Finally, I look at the consumption and credit card debt repayment surrounding mortgage delinquency. I find that households decrease their consumption at default, but at the same time repay their credit card debt. Instead of using consumer credit as a means to smooth consumption, households seem to more concerned about preserving their access to credit.

These results emphasize the important role of households savings in liquid assets on mortgage default. Policies that encourage more liquid savings, such as escrow accounts may be useful in providing households with the buffer to withstand income shocks.

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Figure 1. Geographic Distribution of Sample Households

This figure shows the distribution of households in each state . Panel A shows the proportion of the total households that reside in each state. The dark bars indicate the percentages for the sample of households used in this paper. The light bars indicate the percentages for the 2010 United States Census. Panel B shows the percentage point differences between the two percentages for each state.

Figure 1: Panel A

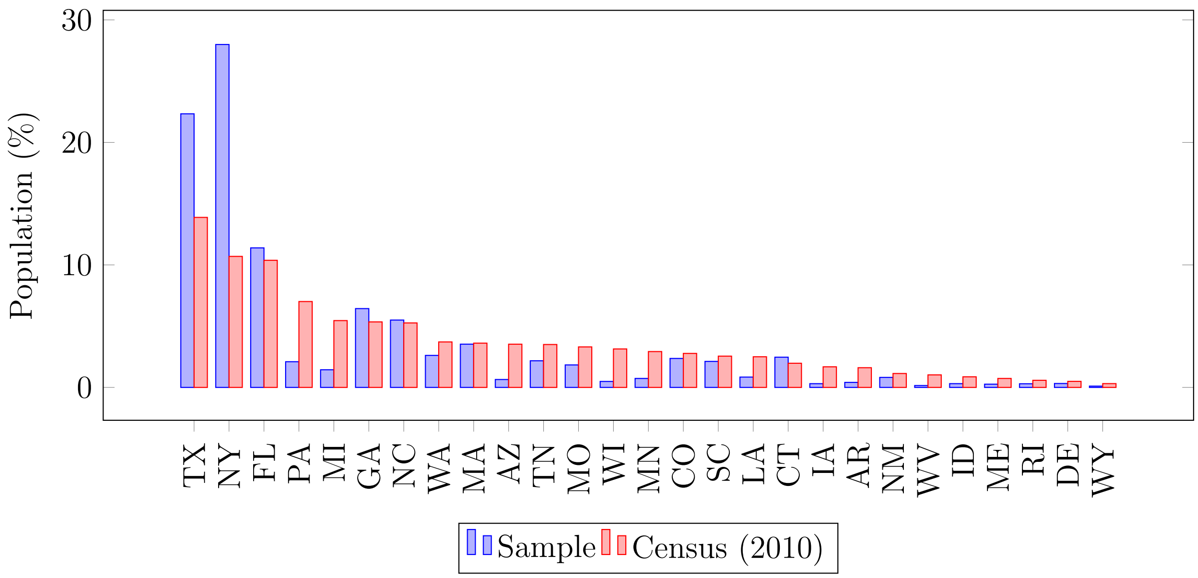

Figure 1: Panel B

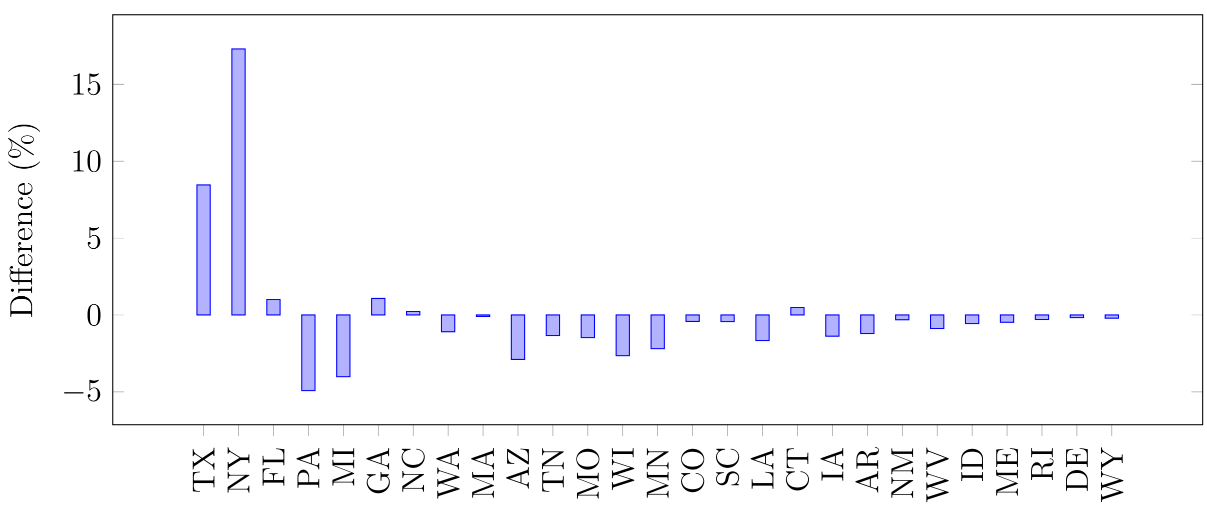

Figure 2. Distribution of Income

This figure shows the distribution of income of the sample, compared to the distribution of income in the 2013 American Housing Survey (AHS) and the 2012 Current Population Survey (CPS). The annual income for the sample are the average monthly income in the pre-period that is annualized. The sample income is after withholdings, so it is biased downward compared to the survey distribution.

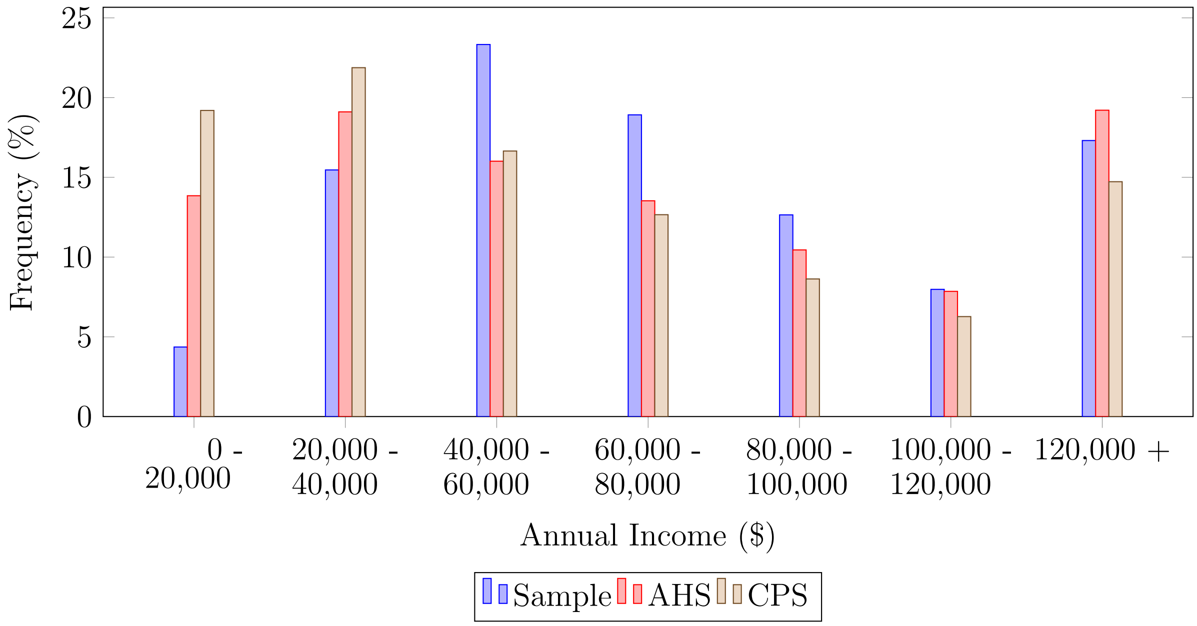

Figure 3. Retail Expenditures Surrounding Mortgage Default

This figure plots the OLS regression coefficients for retail consumption surrounding mortgage default. The regressions use a difference-in-differences design where the consumption for a particular month for households that default are compared to the consumption for households that do not default for the same month. The omitted variable is the all months prior to 6 months before default. Standard errors are clustered by household and year-month. The vertical lines represent 95% confidence intervals. The confidence intervals for the mid savings in Panel B are dropped for visual clarity.

Figure 4: Panel A

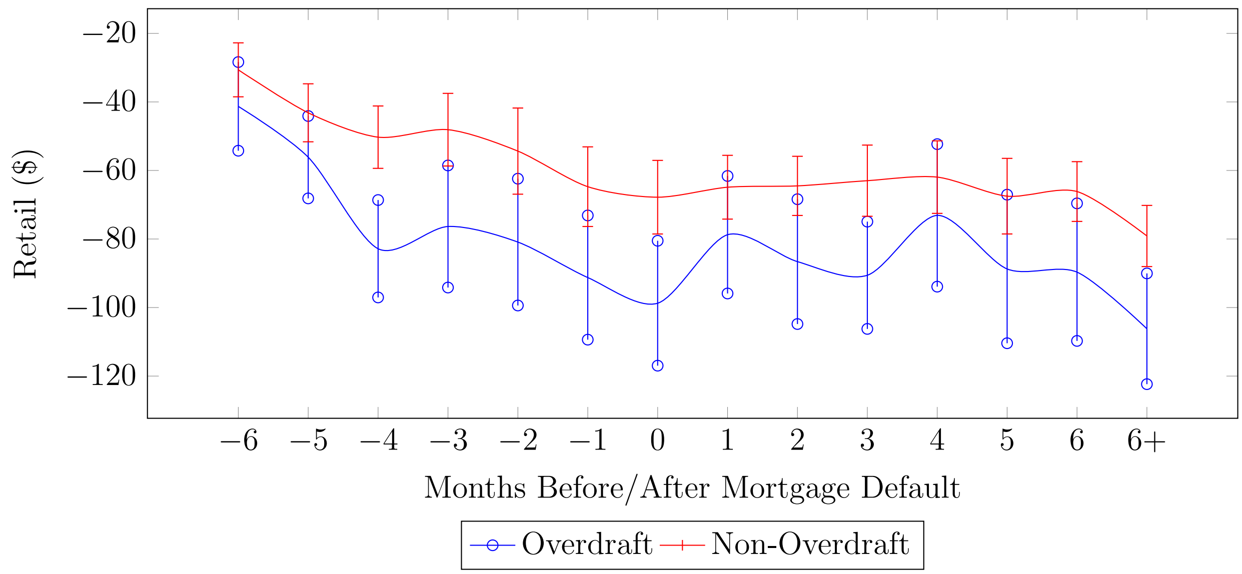

Figure 4: Panel B

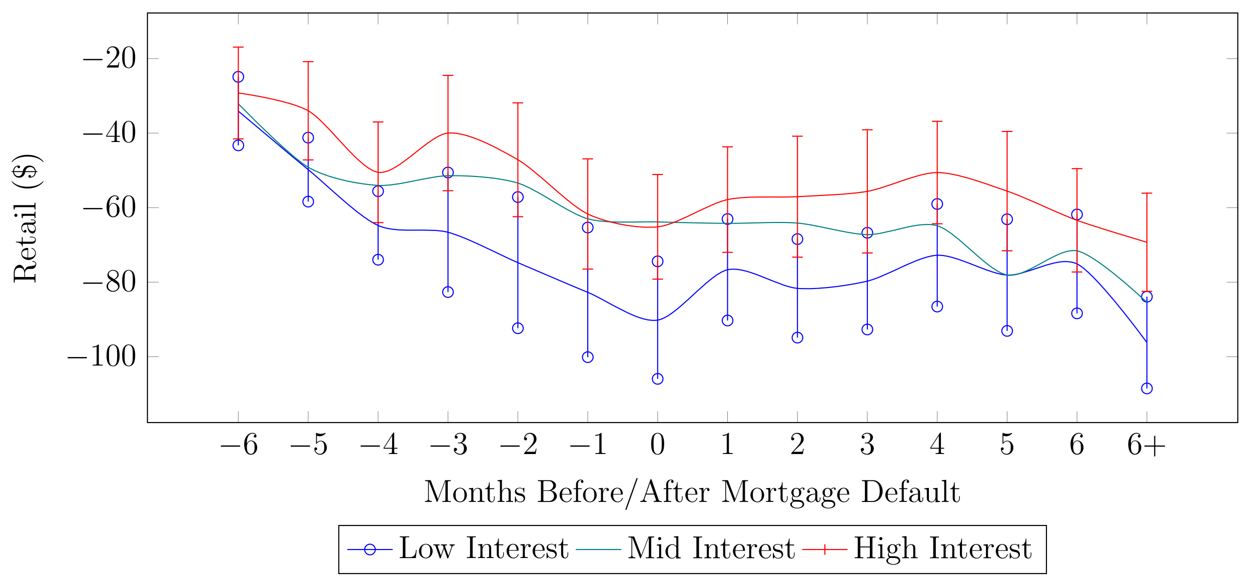

Figure 4. Restaurant Expenditures Surrounding Mortgage Default

This figure plots the OLS regression coefficients for restaurant consumption surrounding mortgage default. The regressions use a difference-in-differences design where the consumption for a particular month for households that default are compared to the consumption for households that do not default for the same month. The omitted variable is the all months prior to 6 months before default. Standard errors are clustered by household and year-month. The vertical lines represent 95% confidence intervals. The confidence intervals for the mid savings in Panel B are dropped for visual clarity.

Figure 5: Panel A

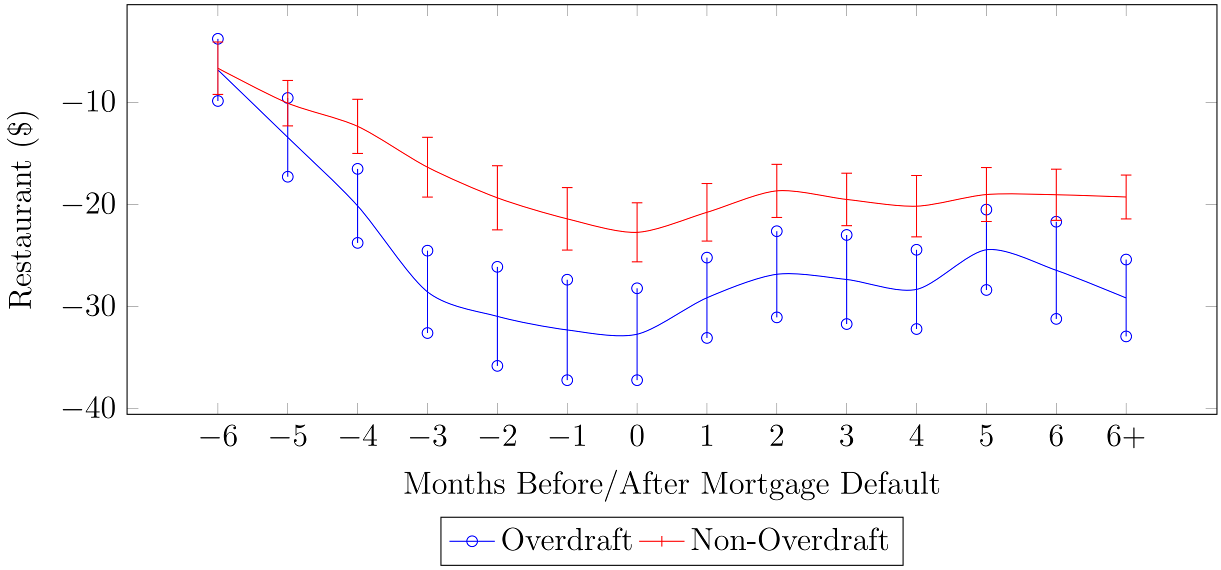

Figure 5: Panel B

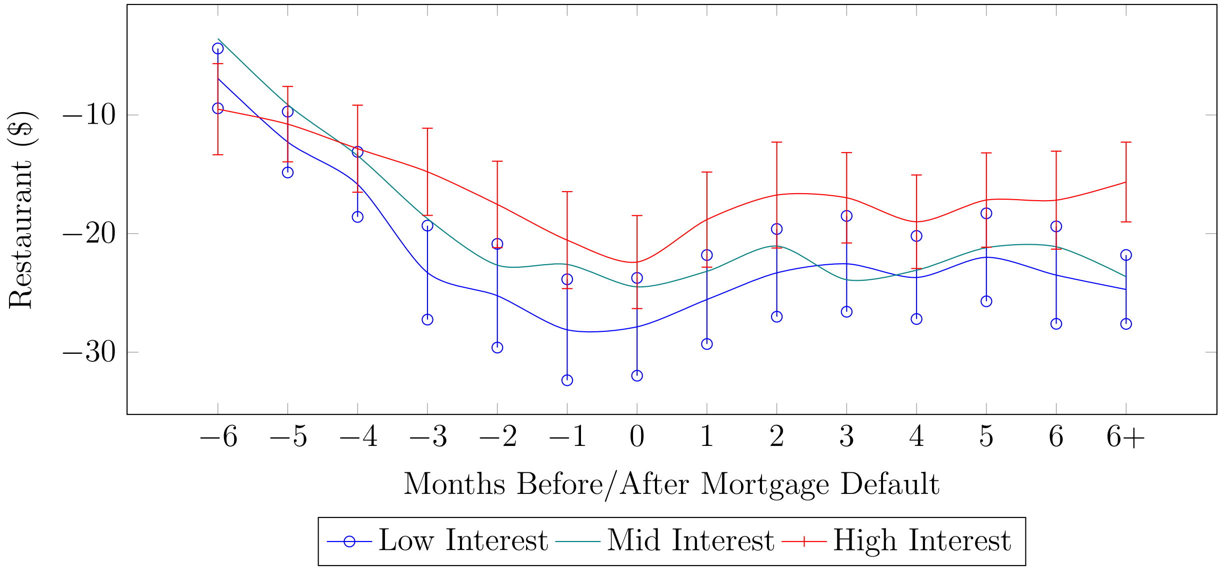

Figure 5. Grocery Expenditures Surrounding Mortgage Default

This figure plots the OLS regression coefficients for grocery consumption surrounding mortgage default. The regressions use a difference-in-differences design where the consumption for a particular month for households that default are compared to the consumption for households that do not default for the same month. The omitted variable is the all months prior to 6 months before default. Standard errors are clustered by household and year-month. The vertical lines represent 95% confidence intervals. The confidence intervals for the mid savings in Panel B are dropped for visual clarity.

Figure 6: Panel A

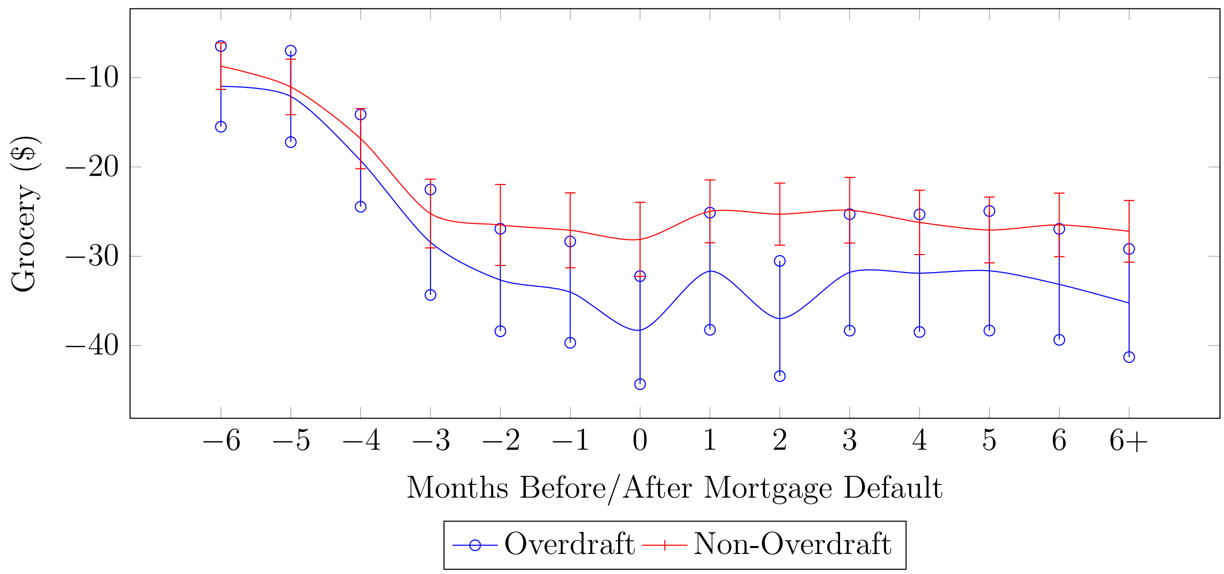

Figure 6: Panel B

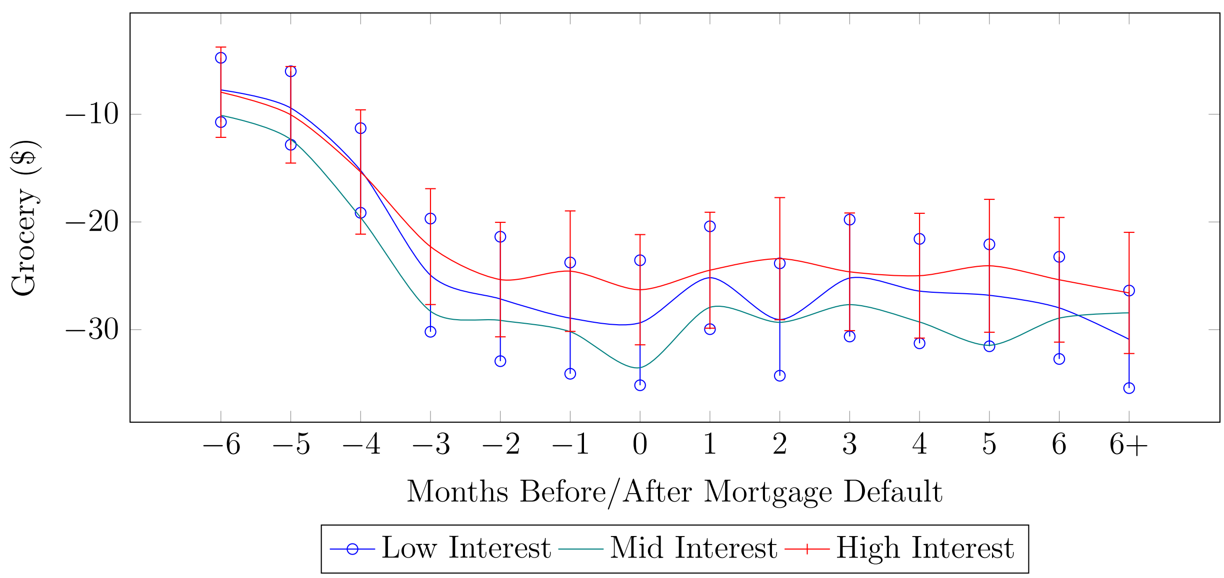

Table 1. Summary Statistics

This table presents the summary statistics for the households in the sample. Panel A shows the summary statistics for all households in the sample. Panel B shows the summary statistics for households that default on their mortgages during the sample period. Panel C shows the summary statistics for households that do not default on their mortgages during the sample period. All variables, except for the number of households, are measured as the monthly average amount in the pre-period for each household. All variables, except for the number of households, are rounded to the nearest dollar unless the amount is less than a dollar, in which case it is rounded to the nearest cent. The pre-period is the 6 month period in which households have both income and mortgage payment transactions.

Table 1: Panel A - All Households

	Mean	StDev	Min	10%	50%	90%	Max
Mortgage Payment	2,035	2,525	1	800	1,612	3,537	839,568
Income	7,660	12,561	0.02	2,483	5,539	12,828	1,324,175
Interest Earned	8	112	0	0	0.36	13	30,281
Brokerage	547	7,617	0	0	0	70	2,501,883
Overdraft Fees	3	26	0	0	0	9	9,309
Consumption							
Retail	413	706	0	0	232	974	66,327
Restaurant	148	484	0	0	94	328	84,172
Grocery	115	284	0	0	16	367	84,522
Households (#)	265,144						

Table 1: Panel B - Defaulting Households

	Mean	StDev	Min	10%	50%	90%	Max
Mortgage Payment	2,049	2,158	1	764	1,578	3,572	83,247
Income	7,757	14,458	2	2,339	5,298	13,026	820,491
Interest Earned	10	221	0	0	0.29	13	30,281
Brokerage	536	9,284	0	0	0	50	1,108,582
Overdraft Fees	5	16	0	0	0	12	635
Consumption							
Retail	369	725	0	0	192	868	50,003
Restaurant	143	362	0	0	90	318	27,410
Grocery	99	199	0	0	10	319	5,129
Households (#)	28,082						

Table 1: Panel C - Non-Defaulting Households

	Mean	StDev	Min	10%	50%	90%	Max
Mortgage Payment	2,033	2,565	1	805	1,617	3,533	839,568
Income	7,648	12,317	0.02	2,500	5,565	12,805	1,324,175
Interest Earned	8	91	0	0	0.37	13	22,085
Brokerage	448	7,394	0	0	0	75	2,501,883
Overdraft Fees	3	27	0	0	0	8	9,309
Consumption							
Retail	418	703	0	0	237	986	66,327
Restaurant	149	496	0	0	94	329	84,173
Grocery	117	293	0	0	16	373	84,521
Households (#)	237,062						

Table 2. Households with Low Liquid Assets

This table presents the proportion of households with low liquid assets. Panel A shows the tercile breakpoints that separates the low-middle interest tecile and middle-high interest tercile, and also the proportion of households in each income tercile that belong in each interest tercile. The dollar breakpoints are the capitalized dollar amount that correspondes to the interest earned. Panel B shows that proportion of households that have incurred overdraft fees, for the entire sample and for each income tercile.

Table 2: Panel A - Proportion of Households in Each Interest & Income Tercile

	Low-interest	Mid-interest	High-interest
Tercile breakpoints ($)	0.103	1.285	
Dollar breakpoints ($)	2,472	30,840	
Low-income (%)	48.5	31.5	20.0
Mid-income (%)	33.6	37.0	29.4
High-income (%)	18.1	31.4	50.5

Table 2: Panel B - Proportion of Households with Overdraft Fees

	Overdrafts	Non-overdrafts
All (%)	19.4	80.6
Low-income (%)	24.1	75.9
Mid-income (%)	19.4	80.6
High-income (%)	14.7	85.3

Table 3. Household Savings and Mortgage Default

This table explores the relationship between household savings and mortgage default. The regressions in this table are dynamic logit models. All regressions include state and year-month fixed effects, changes in regional real estate prices, and a fifth-order polynomial in account age as controls. The regression coefficients are expressed in terms of relative risk. Mortgage delinquency equals one if a household is more than three months delinquent on its mortgage. Overdraft is a dummy that equals one if the household incurred overdraft fees during the pre-period. Brokerage is a dummy that equals one if the household had transactions with a financial brokerage or mutual fund companies during the pre-period. Low interest, mid interest, and high interest are dummies that equal one if the interest that the household received during the pre-period belongs in the low, middle, high tercile of households, respectively. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default				
	(1)	(2)	(3)	(4)	(5)
Overdraft	1.43***				1.31***
	(0.02)				(0.02)
Brokerage		0.78***			0.80***
		(0.01)			(0.01)
Low Interest			1.43***		1.34***
			(0.02)		(0.02)
Mid Interest				0.74***	
				(0.01)	
High Interest				0.66***	
				(0.01)	
State FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
No. Obs.	7,660,189	7,660,189	7,660,189	7,660,189	7,660,189
Log Pseudolikelihood	-173,189	-173,331	-173,078	-173,051	-172,835
Pseudo-R^2	0.01	0.01	0.02	0.02	0.02

Table 4. Income, Spending, Mortgage-to-Income, and Mortgage Default

This table explores the relationship between other household characteristics and mortgage default. The regressions in this table are dynamic logit models. All regressions include state and year-month fixed effects, changes in regional real estate prices, and a fifth-order polynomial in account age as controls. The regression coefficients are expressed in terms of relative risk. Mortgage default equals one if a household is more than three months delinquent on its mortgage. Low income, mid income, and high income are dummies that equal one if the average household income in the pre-period belong in the low, middle, high tercile of households, respectively. High spending is a dummy that equals one if the ratio of consumption to income is in the high tercile of households in the pre-period. High Mortgage-to-Income is a dummy that equals one if the mortgage payment to income ratio for the household is in the high tercile of households in the pre-period. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default				
	(1)	(2)	(3)	(4)	(5)
Low Income	1.24***				1.14***
	(0.02)				(0.02)
Mid Income		0.83***			
		(0.01)			
High Income		0.78***			
		(0.01)			
High Spending			1.03***		0.95
			(0.02)		(0.02)
High Mortgage/Income				1.12***	1.03***
				(0.02)	(0.02)
Overdraft					1.32***
					(0.02)
Brokerage					0.81***
					(0.02)
Low Interest					1.32***
					(0.02)
State FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
No. Obs.	7,660,189	7,660,189	6,989,505	7,660,189	6,989,505
Log Pseudolikelihood	-173,305	-173,299	-158,526	-173,404	-157,862
Pseudo-R^2	0.01	0.01	0.01	0.02	

Table 5. Unemployment, Household Savings, and Mortgage Default

This table explores the relationship between unemployment, household savings, and mortgage default. The regressions in this table are dynamic logit models. All regressions include state and year-month fixed effects, changes in regional real estate prices, and a fifth-order polynomial in account age as controls. The regression coefficients are expressed in terms of relative risk. Mortgage default equals one if a household is more than three months delinquent on its mortgage. Unemployment & Overdraft is a dummy variable that equals one if the household had incurred overdraft fees in the pre-period and if the household is unemployed in the current month. The definitions are similar for other variables. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default		
	(1)	(2)	(3)
Unemployment & Overdraft	2.60***		
	(0.23)		
Unemployment & Non-Overdraft	1.50***		
	(0.09)		
Unemployment & Brokerage		1.26*	
		(0.17)	
Unemployment & Non-Brokerage		1.82***	
		(0.10)	
Unemployment & Low Interest			1.97***
			(0.15)
Unemployment & Mid Interest			1.96***
			(0.16)
Unemployment & High Interest			1.23**
			(0.12)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
No. Obs.	7,660,189	7,660,189	7,660,189
Log Pseudolikelihood	-173,374	-173,383	-173,377
Pseudo-R^2	0.01	0.01	0.01

Table 6. Unemployment, Income, Spending, MTI, and Mortgage Default

This table explores the relationship between unemployment, other household characteristics, and mortgage default. The regressions in this table are dynamic logit models. All regressions include state and year-month fixed effects, changes in regional real estate prices, and a fifth-order polynomial in account age as controls. The regression coefficients are expressed in terms of relative risk. Mortgage default equals one if a household is more than three months delinquent on its mortgage. Unemployment & Low Income is a dummy variable that equals one if the household belonged in the low income tercile in the pre-period and if the household is unemployed in the current month. The definitions are similar for other variables. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default		
	(1)	(2)	(3)
Unemployment & Low Income	1.81***		
	(0.13)		
Unemployment & Mid Income	1.68***		
	(0.15)		
Unemployment & High income	1.59***		
	(0.16)		
Unemployment & Low Spending		1.79***	
		(0.15)	
Unemployment & Mid Spending		1.80***	
		(0.16)	
Unemployment & High Spending		1.80***	
		(0.17)	
Unemployment & Low Mortgage/Income			1.54***
			(0.15)
Unemployment & Mid Mortgage/Income			1.88***
			(0.16)
Unemployment & High Mortgage/Income			1.72***
			(0.13)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
No. Obs.	7,660,189	7,660,189	7,660,189
Log Pseudolikelihood	-173,386	-173,383	-173,386
Pseudo-R^2	0.01	0.01	0.01

Table 7. Overdrafts vs. Income, Spending, and Mortgage-to-Income

This table explores the effect of overdrafts against income, spending, and mortgage-to-income on mortgage default. The regressions in this table are dynamic logit models. All regressions include state and year-month fixed effects, a fifth-order polynomial in account age, and the changes in regional real estate prices as controls. The regression coefficients are expressed in terms of relative risk. Mortgage default equals one if a household is more than three months delinquent on its mortgage. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default		
	Category:		
	Income	Spending	MTI
	(1)	(2)	(3)
Overdraft & Low Category	1.77***	1.42***	1.34***
	(0.04)	(0.04)	(0.04)
Overdraft & Mid Category	1.43***	1.41***	1.44***
	(0.04)	(0.03)	(0.04)
Overdraft & High Category	1.20***	1.47***	1.64***
	(0.04)	(0.04)	(0.04)
Non-Overdraft & Low Category	1.17***	1.00	1.02
	(0.02)	(0.02)	(0.02)
Non-Overdraft & Mid Category			
Non-Overdraft & High Category	0.98	0.98	1.09***
	(0.02)	(0.02)	(0.02)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
No. Obs.	7,660,189	7,660,189	7,660,189
Log Pseudolikelihood	-173,027	-173,151	-173,124
Pseudo-R^2	0.02	0.01	0.02

Table 8. Savings vs. Income, Spending, and Mortgage-to-Income

This table explores the effect of savings against income, spending, and mortgage-to-income on mortgage default. The regressions in this table are dynamic logit models. All regressions include state and year-month fixed effects, a fifth-order polynomial in account age, and the changes in regional real estate prices as controls. The regression coefficients are expressed in terms of relative risk. Mortgage default equals one if a household is more than three months delinquent on its mortgage. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default		
	Income	Category: Spending	MTI
	(1)	(2)	(3)
Low Interest & Low Category	1.53***	1.34***	1.31***
	(0.04)	(0.03)	(0.04)
Low Interest & Mid Category	1.23***	1.35***	1.33***
	(0.03)	(0.03)	(0.04)
Low Interest & High Category	1.17***	1.38***	1.47***
	(0.04)	(0.03)	(0.04)
Mid Interest & Low Category	1.08***	1.04	0.98
	(0.03)	(0.02)	(0.03)
Mid Interest & Mid Category			
Mid Interest & High Category	0.97	0.95*	1.06**
	(0.03)	(0.02)	(0.03)
High Interest & Low Category	0.97	0.89***	0.94***
	(0.03)	(0.02)	(0.02)
High Interest & Mid Category	0.84***	0.85***	0.84***
	(0.02)	(0.02)	(0.02)
High Interest & High Category	0.91***	0.85***	0.93***
	(0.02)	(0.03)	(0.03)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
No. Obs.	7,660,189	7,660,189	7,660,189
Log Pseudolikelihood	-172,189	-173,032	-173,024
Pseudo-R^2	0.02	0.02	0.02

Table 9. Unemployment vs. Overdrafts vs. Income

This table explores the effect of savings and unemployment against income on mortgage default. The regression in this table are dynamic logit models. The regression include state and year-month fixed effects, a fifth-order polynomial in account age, and the changes in regional real estate prices as controls. The regression coefficients are expressed in terms of relative risk. Mortgage default equals one if a household is more than three months delinquent on its mortgage. All numbers in this table are from a single regression with one omitted variable. Standard errors are clustered at the household level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mortgage Default		
	Low Income	Mid Income	High Income
Employed & Overdraft	1.76***	1.42***	1.20***
	(0.04)	(0.04)	(0.04)
Employed & Non-Overdraft	1.16***		0.98
	(0.02)		(0.02)
Unemployed & Overdraft	2.90***	3.11***	2.69***
	(0.35)	(0.52)	(0.59)
Unemployed & Non-Overdraft	1.74***	1.60***	1.59***
	(0.15)	(0.18)	(0.18)
State FE		Yes	
Time FE		Yes	
Controls		Yes	
No. Obs.		7,660,189	
Log Pseudolikelihood		-172,980	
Pseudo-R^2		0.02	

Table 10. Credit Card Debt Repayment Surrounding Mortgage Default

This table explores credit card debt repayment surrounding mortgage default. The regressions in this table are OLS regressions, that use a difference-in-differences design where the debt repayment for a particular month for households that become delinquent are compared to the debt repayment for households that do not become delinquent for the same month. I(t $\geq Q_{-2}$) is a dummy variable for all months in and after the second quarter before default. I(t $= Q_t$) are dummy variable for the months in quarter t. I(t $> Q_2$) is a dummy variable for all months following the second month after default. Credit card debt repayment is the sum of all credit transactions for the current month less the sum of all debit transactions for the prior month, for the household's credit card accounts. The omitted variable is the all months prior to 6 months before default. Standard errors are clustered at the household and year-month level, and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Panel A - Overdrafts and Credit Card Debt Repayment

	Credit Card Debt Repayment ($)			
	Subsample: Overdraft		Subsample: Non-Overdraft	
	(1)	(2)	(3)	(4)
I(t $\geq Q_{-2}$)	12.11***		7.74***	
	(4.42)		(2.65)	
I(t $= Q_{-2}$)		3.82		2.44
		(5.85)		(4.86)
I(t $= Q_{-1}$)		24.90***		19.21***
		(6.09)		(4.38)
I(t $= Q_0$)		12.16*		−3.68
		(6.61)		(5.30)
I(t $= Q_1$)		17.81**		2.75
		(7.34)		(6.11)
I(t $= Q_2$)		10.09*		14.55***
		(5.22)		(5.81)
I(t $> Q_2$)		8.39		9.53***
		(6.77)		(3.30)
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. Obs.	2,649,160	2,649,160	10,338,134	10,338,134
R^2	0.02	0.02	0.02	0.02

Table 10: Panel B - Savings and Credit Card Debt Repayment

	Credit Card Debt Repayment ($)					
	Subsample:					
	Low Savings		Mid Savings		High Savings	
	(1)	(2)	(3)	(4)	(5)	(6)
I(t $\geq Q_{-2}$)	15.97***		6.21*		3.76	
	(4.02)		(3.55)		(3.47)	
I(t $= Q_{-2}$)		6.49		−5.68		8.19
		(5.67)		(6.53)		(8.02)
I(t $= Q_{-1}$)		26.64***		24.67***		9.39
		(4.52)		(7.26)		(6.96)
I(t $= Q_0$)		11.21**		2.59		−15.74**
		(5.07)		(8.37)		(6.50)
I(t $= Q_1$)		18.64***		5.16		−5.56
		(6.57)		(8.28)		(8.37)
I(t $= Q_2$)		20.64***		0.60		19.90**
		(5.19)		(6.85)		(9.03)
I(t $> Q_2$)		15.42**		6.96*		5.43
		(6.76)		(3.82)		(4.30)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	4,351,982	4,351,982	4,473,961	4,473,961	4,161,351	4,161,351
R^2	0.02	0.02	0.02	0.02	0.02	0.02