# Financial Breakups: Till Debt Do Us Part*

Alexander W. Butler† Ioannis Spyridopoulos‡ Yessenia C. Tellez§

Billy Y. Xu¶

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Using a large representative sample of individual credit bureau records, we document that personal financial distress increases a married couple's probability of divorce by 4%-8%. Foreclosures strongly affect marital dissolution, whereas Chapter 13 bankruptcies, which protect debtors from foreclosure, have the opposite effect. These effects of foreclosure and bankruptcy protection on household stability are distinct from health- or employment-related shocks. We isolate plausibly exogenous variation in the probability of foreclosure by exploiting financial assistance programs that protect homeowners after natural disasters. Our findings highlight the role of financial stability and housing security as determinants of family structures and suggest that household finances have broad social consequences.

**JEL Codes**: D14, J12, G51, I31, R28, K36

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## 1. Introduction

If one wants to divorce oneself from romanticism, an approach to studying the institution of marriage is through an economic lens (Becker (1973, 1974, 1991)). That economics lens view marriage as a utility-maximizing transaction between two willing participants competing with potential suitors in the marriage market. The utility gain of marriage depends on the partners' income and human capital. People marry when the expected utility of marriage exceeds the expected utility of being single (Becker, Landes, Michael (1977)). In such a world of expected utility maximization, the dissolution of marriage is perhaps best understood as resulting from events not fully anticipated at the time of marriage.

One important source of uncertainty that may impact the expected utility of being married is a person's financial health. Our paper uses a panel of micro-data on individuals' financial health and marriage status to examine how different types of financial distress impact marital dissolution choices. The financial stability of households is a key concern for policymakers and regulators due to its direct impact on consumer demand (Mian, Rao, and Sufi (2013), Mian, Sufi, and Trebbia (2010), Mian, Sufi, and Trebbi (2015), and Mian and Sufi (2014)). Recent research suggests that financial distress may also have significant personal and social effects on individuals, such as physical and mental health, productivity, criminal behavior, and childbearing decisions (Garmaise and Moskowitz (2006), Engelberg and Parsons (2016), Carrell and Zinman (2014), Bernstein, McQuade, and Townsend (2021), Maturana and Nickerson (2019), and Hacamo (2021)). These social consequences have welfare implications (Chetty, Hendren, Kline, and Saez (2014) and Knüpfer, Rantala, Vihriälä, and Vokata (2023)), suggesting that the overall costs associated with household financial distress may be larger than previously thought.

We examine the relation between financial distress and divorce because, ex ante, it is not clear what direction the effect might be. On the one hand, financial distress can lead to an increase in the likelihood of divorce if the distress decreases a couple's expected gain from remaining married and increases the variance of the distribution of unanticipated gains from marriage (Becker, Landes, and Michael (1977)). On the other hand, a couple facing financial hardship may be less likely to divorce if they believe that their combined wealth when divorced will likely not exceed their combined married-wealth (Becker, Landes, and Michael (1977)) due to a loss of their ability to share costs and diversify labor income risks (Shore, 2010). Furthermore, divorces are expensive to initiate and impose large economic and personal costs on families, especially for women and children (e.g., Tach and Eads (2015) and McLanahan, Tach, and Schneider (2013)). Financial distress can exacerbate the disutility women face during divorce and disincentivize their preference for marital dissolution, as women have historically experienced disproportionate economic costs during divorces, such as inadequate post-dissolution transfers (e.g., insufficient child support awards) and inequalities in ex-post labor market outcomes (e.g., Holden and Smock (1991) and Leopold (2018)).[1] Thus, while financial distress may contribute to various personal and social effects, its direct influence on divorce rates remains ambiguous.

In this study, we investigate how individuals' financial distress affects households' marital instability. Using micro-level data from a large sample of individuals' credit histories and marital statuses, we show that negative financial shocks strongly predict the incidence of divorce.[2] Married individuals who experience foreclosures or have delinquencies and debt in collections have a higher probability of getting a divorce in the following year by

[1] Other studies show that positive financial windfalls have opposite impacts on the marriage rates for men and women (Bertrand, Kamenica, and Pan (2015); Cesarini, Lindqvist, O¨ stling, and Terskaya (2023)).
[2] Research in family studies and sociology have relied on data from small surveys to examine the relationship between financial disagreements and divorce (e.g., Gudmunson, Beutler, Israelsen, McCoy, and Hill (2007), Britt, Grable, Goff, and White (2008), Dew (2011), Dew, Britt, and Huston (2012), and Britt and Huston (2012)).

approximately 0.3-0.6 percentage points, a 4%-8% increase in the average annual divorce rate in our sample. This finding suggests a strong association between financial and marital stress.

We start by examining potential mechanisms through which financial distress affects marital relationships. The occurrence of delinquencies, debt in collections, and foreclosures are positively associated with divorce. Among several financial distress indicators, we show that foreclosure is the strongest predictor of divorce outcomes. This result is consistent with theory suggesting that marriage-specific assets like houses provide more utility when couples stay married (Becker, Landes, and Michael (1977)), and thus the loss of such assets due to foreclosure impairs partners' commitment to marriage (Lafortune and Low (2017)).

Further evidence that housing instability increases the probability of divorce comes from the differential protection of homes under Chapter 7 and Chapter 13 of the bankruptcy code. Under Chapter 7 bankruptcy protection, households liquidate their homes and consequently are more likely to divorce on average, although the effects are statistically insignificant. However, Chapter 13 bankruptcy protection allows homeowners to keep their homes after reaching a deal with their creditors. In addition, by discharging the unsecured debt, borrowers can reallocate household income to pay their outstanding mortgage debt and prevent the sale of their homes. We find that filing for bankruptcy under Chapter 13 induces the opposite outcome than Chapter 7: the probability of divorce declines by 0.58 percentage points, an eight percent decrease in the likelihood of divorce relative to the unconditional mean. Overall, these results illustrate the importance of housing stability as a key mechanism through which financial distress affects marital stress.

Identifying the impact of financial distress on marital distress has several empirical challenges. First, unobservable shocks such as health shocks commonly correlate with financial and personal distress and may drive the effect of financial distress on divorces (e.g., Lillard and Waite (1995), Daniel, Wolfe, Busch, and McKevitt (2009), and Teachman (2010)). Our data include information about medical debt in collections, which we control for in our tests. In addition, financial distress may be correlated with unobservable personality traits that drive divorce decisions rather than financial strain. We incorporate restrictive individual fixed effects to mitigate the impact of time-invariant aspects of an individual's personality on divorce choices. In addition, the results remain robust using non-linear models of financial distress or accounting for contemporaneous local economic shocks using restrictive tract-year fixed effects.

To isolate the effects of financial distress from other confounding factors or reverse causality, we use an instrumental variables approach by exploiting natural disaster assistance programs (i.e., natural disaster credit reporting relief) that protect homeowners from foreclosure. We find that these programs effectively provide financial support to affected individuals, increasing their credit access and maintaining their credit scores. The impact of natural disasters on individuals' financial health is largely unpredictable, especially after we condition on year and individual fixed effects. Thus, the variation in foreclosure rates between individuals (after accounting for a host of individual attributes) is plausibly exogenous. Our findings suggest that a reduction in the probability of foreclosure deriving from disaster assistance reduces the probability of divorce by one percentage point—a 15% drop in the sample mean.

This paper contributes to the current literature in three distinct yet interrelated dimensions. Primarily, our study adds to the evidence of the relationship between household finances and individuals' welfare. For instance, previous studies suggest that financial loss has a negative impact on anxiety and depression (Engelberg and Parsons (2016)), crime (Garmaise and Moskowitz (2006), and Huck (2018)), job performance and productivity

(Maturana and Nickerson (2019) and Bernstein, McQuade, and Townsend (2021)), food insecurity (Butler, Demirci, Gurun, and Tellez, (2023)), voting (McCartney (2021)), and childbearing (Hacamo (2021)). Our findings underscore the importance of financial and housing security on households' marital stability, suggesting that we may be underestimating the overall costs of financial distress.

Secondly, our study emphasizes the role of housing stability as a channel through which financial health affects marital status. This relationship complements the findings of Hacamo (2021), who demonstrates that expanded access to mortgage financing increases homeownership and, consequently, families' decisions to have children. Moreover, these findings indicate substantial social costs associated with foreclosures, thus contributing to ongoing debates about foreclosure policies that promote housing stability.[3] The relevance of these findings is further heightened by existing research suggesting that family stability is a vital predictor of children's outcomes and intergenerational economic mobility (Becker, (1991) and Chetty, Hendren, Kline, and Saez, (2014)).

Finally, the results of the study offer a strong argument suggesting that financial distress is not merely a consequence of personal turmoil or misfortune, but it plays a direct role in households' happiness and stability. Prior research has identified that family status can influence financial outcomes, including asset allocation, investment management, cumulative wealth, and homeownership (Love (2010); Lu, Ray, and Teo, (2016); Hubener, Maurer, and Mitchell, (2016); Fischer and Khorunzhina, (2019)). Recent studies corroborate the significant impact of financial status on marital stability and quality. Segeyev, Lian, and Gorodnichenko (2023) document the psychological impact of financial stress, its role in

[3] According to the U.S. Census of Public Finance, the U.S. States and local governments annually spend 60 billion dollars on housing programs that aim to support homeowners in financial distress. Housing support is one of the top three spending categories with the highest annual growth rate: https://urbn.is/3wLH3YW.

creating poverty traps, and its potential macroeconomic implications, reinforcing the link between financial health and broader social outcomes. Olson, Rick, Small, and Finkel (2023) demonstrate that financial interdependence in the form of joining banking accounts improves relationship quality in newlyweds. Lastly, Cesarini, Lindqvist, Östling, and Terskaya (2023) provide evidence that financial resources affect marriage formation, fertility, and divorce risk, especially among males, which aligns with our findings on the role of financial stability and housing security in determining family structures. Consistent with theory (Becker, Landes, and Michael (1977)) and references in the media, our study is the first, to the best of our knowledge, to use a large representative sample of non-survey credit bureau records to illustrate how financial distress affects households' stress.

## 2. Data and Methods

### 2.1. Data and summary

We construct our main sample with a one percent nationally representative sample of the U.S. population with credit bureau records from 2011 to 2019.[4] The credit bureau data provide a panel of credit histories for over 3 million individuals and include detailed information on individuals' credit scores, mortgages, auto loans, credit cards, student loans, repayment patterns, delinquencies, and debt collections. In addition, our sample contains basic demographic information for individuals, including their marital status, estimated household income, gender, and age.

We use marital divorce as our main outcome variable. Previous research documents that marriage has a larger impact on longevity than income (Gardner and Oswald (2004) and Simeonova (2013)). Therefore, we consider the individuals' marital status a reasonable proxy

[4] The sample selection is random and based on individuals' last two digits of their social security numbers.

of personal stress. We identify whether an individual becomes divorced if their marital status in the current year changes from married to single. The average divorce rate represents the unconditional probability of getting a divorce in a given year and is approximately equal to 6.8% in our sample. For further validation, we compare state-level marriage rates in 2015 between our sample and census data. The correlation coefficient of marital status in our sample with that of 1-year American Community Survey estimates is 0.84.

We construct several proxies of financial distress to capture varying levels of financial strain. First, we construct *Bankruptcy*, which is an indicator variable that equals one when an individual had a bankruptcy filing in the last 12 months and zero otherwise. Fewer than 1% of individuals in our sample experience a bankruptcy event during the 9-year sample period. We also identify individuals that go through foreclosure proceedings or auto repossessions. Bankruptcies are the most severe indicators of financial stress, but foreclosures are almost as severe in terms of initial credit score impact.

A less severe measure of financial distress is debt in collections. We construct *High Collections (Non-Med)*, which is an indicator variable that equals one for individuals whose debt in collections (non-medical) is in the top tercile of the annual distribution of positive non-medical debt in collections, and zero otherwise. Having debt in collections may impose a smaller burden on households than bankruptcies, foreclosures, and repossessions. On average, 23% of observations in our sample have outstanding debt in collections.[5] Finally, we examine the effects of *Being Delinquent*, a variable that equals one if the individual has been delinquent in payments over the last 12 months and zero otherwise.

We complement our sample with economic, real estate, and demographic

[5] According to a report by the Consumer Financial Protection Bureau (CFPB), one in four consumers in the United States has at least one debt in collection in their credit report. See the CFPB report in the following link: https://www.consumerfinance.gov/about-us/newsroom/bureau-releases-report-third-party-debt-collections/

characteristics of individuals' local communities using data from the Census Bureau's American Community Survey (ACS). Specifically, we add controls for Census tract-level population density, poverty rate, the share of minorities, government employment rate, average household size, and the presence of children in the family. These characteristics capture time-varying factors that may be correlated with divorce rates. Although these control variables may not fully capture an individual's economic or demographic status in our sample, they should partially account for individuals' local employment conditions and our financial distress measures then capture the variation not explained by these regional factors.

We exclude from the analysis individual-year observations with missing information on marital status, credit score, gender, age, and financial and social stress variables. Our final sample contains 2.0 million people, covering approximately 90% of all counties in the country. Table 1 shows the summary statistics of the variables in our analysis. The median individual in our sample is 52 years old, has an average estimated household income of $98,000 a year, an average credit score of 700, and owes an average of $94,000 in total debt (e.g., mortgage, auto, credit, and student). The average borrower owes $76,000 in mortgage debt, $6,000 in auto loans, and $4,400 in credit card debt.

[Insert Table 1]

Borrowers who experience a divorce in a given year have substantially higher financial distress levels than those who remain married. Columns (1)-(3) of Table 2 show univariate differences between individuals who experience divorce versus individuals who did not in a given year. The average ratios of delinquency, debt in collections, and credit card utilization are substantially higher for individuals who experience divorce. For example, 44% of individuals who get a divorce also have debt in collections, compared to 21% in the group of individuals with no divorce. On average, individuals who experience divorce have higher credit card utilization (42% versus 30%), lower credit scores (633 versus 705), and lower estimated household incomes ($63,000 versus $101,000) relative to borrowers who did not experience divorce in a given year. Columns (4)-(5) of Table 2 show that individuals who experience severe financial distress are 3 percentage points more likely to divorce (44% of the unconditional mean).

[Insert Table 2]

# 3. Empirical Results

## 3.1. Financial distress and divorce

We examine the impact of financial distress on individuals' probability of divorce using the following baseline regression specification:

$$Divorce_{i,l,t} = \alpha_i + \alpha_t + \delta(Financial\ distress)_{i,l,t-1} + \beta \mathbf{X}_{i,l,t-1} + \gamma \mathbf{C}_{l,t} + \epsilon_{i,l,t}, , \quad (1)$$

where $i$, $t$, and $l$ represent individual, year, and local geography (e.g., census tract), respectively. **X** is a vector of individual-level controls (e.g., age, the natural logarithm of household income and credit score bins, and homeownership indicator) that correlate with the probability of divorce and financial stress. **C** is a vector of tract-level controls that capture different aspects of individuals' local economic environment and includes the following variables: poverty rate, natural log of population density, minority share, average household size, as well as the proportion of households with children, with high school diploma, and with government employees. To ensure that all individuals in our sample can get a divorce, we restrict our sample to individuals that are married in the year prior to experiencing financial distress.

We start the analysis with a definition of financial distress that incorporates the most severe measures of household financial strain. *Financial Distress Event* equals one if an individual experiences bankruptcy, a foreclosure, or auto repossession, and zero otherwise.[6] Table 3 reports our estimates for different empirical specifications. Based on the baseline estimates, major financial distress events increase the probability of divorce by 0.28 percentage points. This change corresponds to approximately a 4%-5% increase in the unconditional probability of divorce in a given year or the equivalent of a 5-10% drop in income. The estimates in Column (1) control for a host of financial and demographic characteristics such as income, homeownership status, and age that previous studies suggest are associated with divorce choices. Columns (2) and (3) present the estimates of regression (1), including $county \times year$ and $tract \times year$ fixed effects, respectively. These models control for unobservable and time-varying local economic and demographic conditions, such as employment status, that affect financial and marital distress. The estimates remain economically similar and thus partially mitigate concerns that unobservable local factors explain the result. We saturate the regressions in Columns (1)-(3) with individual fixed effects. This approach allows us to mitigate the effects of personality traits and time-invariant household attitudes on marital decisions.

[Insert Table 3]

We can assess the extent to which our estimates are the result of omitted variables using the approach developed by Altonji, Elder, and Taber (2005) and extended by Oster (2019). Using granular geographic fixed effects and year interactions or high-dimensional individual fixed effects may not sufficiently capture the effect of unobservable health- or employment-related shocks. Using individual controls such as medical debt in collections, income, and credit score can mitigate part of the omitted variable bias in our estimates, but

[6] We note that an individual's credit score is, in most cases, negatively impacted in the year prior to bankruptcy or foreclosure. Therefore, we do not lag bankruptcy or foreclosure variables in our analysis.

not entirely. However, the bias in the estimates depends on the importance of the factor that is missing from the model. For instance, incorporating an omitted variable in the regression may reduce the effect of financial distress down to zero if this variable is highly correlated with divorce and financial distress. However, the omitted variable may also reduce the estimated effect of financial distress, yet not entirely. In this regard, we estimate how important an omitted variable, such as loss of employment, has to be relative to our existing control variables to wipe out the entire effect of financial distress on divorce. Following the approach of Altonji, Elder, and Taber (2005) and Oster (2019), we estimate that the effect of an idiosyncratic shock to divorce we omit from the model has to be at least 244% better at explaining divorce outcomes than income, credit score, age, gender, and homeownership status combined (or 85% better compared with all control variables and fixed effects combined). Based on these estimates, it seems unlikely that an idiosyncratic omitted shock would have such a large predictive power on divorce choices.

Lastly, there are additional challenges to estimating financial distress's effect on divorce probability. First, the costs associated with divorce are high and may drive the positive association between personal stress and financial distress. Whereas divorces undoubtedly affect financial health, reverse causality is unlikely to drive the estimates in this specific setting. Specifically, our model in regression (1) uses indicators of lagged financial distress. As a result, it is unlikely that future life events (anticipated or not) affect financial distress in previous years unless households act strategically in anticipation of the divorce. We discuss considerations of such identification challenges in later subsections.

### 3.2. Foreclosure and financial distress

The results in Table 3 provide evidence for the impact of financial distress on the probability of divorce on the extensive margin. However, not all kinds of financial distress may create equal stress in households. For instance, small amounts of debt in collections or minor delinquencies are not as stressful as bankruptcies, foreclosures, or repossessions. To test this hypothesis, we use detailed information on individuals' credit balances and repayment history to examine the intensive margin of the relationship between financial and personal distress. To this end, micro-level data facilitate our identification because they allow us to exploit heterogeneity in the type of financial distress among distressed individuals.

Specifically, we break down financial distress into five categories and examine (a) whether there is an intensive-margin effect of financial distress on personal stress and (b) potential mechanisms through which financial distress affects marital dissolution. First, we dissect financial distress into five categories and include each credit event separately in our regression (1): *Bankruptcy*, *Foreclosure*, *Repossession*, *High Collections (Non-Med)*, and *Being Delinquent*.[7] We present the results in Columns (1)-(6) of Table 4.

[Insert Table 4]

The results show several striking patterns. Even though bankruptcy and foreclosure are the biggest indicators of financial distress for individuals, they have diametrically different effects on the probability of divorce. Households that go through foreclosures are 0.50 percentage points more likely to become divorced, an eight percent increase from the unconditional probability of divorce (Column 1). This finding emphasizes the vital role of housing stability on family structures (Becker, Landes, and Michael (1977) and Lafortune and Low (2017)). Importantly, we find that personal bankruptcies do not significantly affect the probability of divorce (Column 5). In addition, we show that individuals who experience an auto repossession in the prior period are not more likely to experience a divorce (Column 2). However, large amounts of non-medical debt in collections and having delinquent debt

[7] We lag *Repossession*, *High Collections (Non-Med)*, and *Being Delinquent* but not *Bankruptcy* and *Foreclosure*.

increase the likelihood that an individual will experience marital dissolution in the following year (Columns 3-4), but the estimated effects are only half of that of foreclosures. The results are almost identical after combining all measures of distress in one regression (Column 6). [8]

We focus on two key implications of these estimates. First, the evidence suggests that not all measures of financial distress have the same impact on marital stability. In particular, delinquencies, high debt in collections, and foreclosures are positively associated with increased divorce risk. Second, even though bankruptcies have the greatest impact on households' financial health, their effect on the probability of divorce is, on average, close to zero. This contrasts with foreclosures, which indicate severe financial distress but to a lesser extent than bankruptcies.[9]

### 3.3. Bankruptcy and financial distress

If financial distress drives divorce outcomes, why are personal bankruptcies, which are leading indicators of households under financial distress, not significantly associated with the probability of divorce? We hypothesize that the mixed results derive from how Chapters 7 and 13 of the U.S. bankruptcy code allow debtors to protect their property from foreclosure. In this section, we exploit the differential treatment of property protection under Chapters 7 and 13 to verify the importance of housing stability on divorce outcomes and to refine the estimates of the effects of bankruptcy on divorce.

Under Chapter 7 of the bankruptcy code, borrowers must show that their income is sufficiently low to discharge unsecured debt such as credit card and medical debt.[10] By discharging the unsecured debt, borrowers can reallocate household income to pay any

[8] We run alternative regressions restricting the sample to females only and find similar results (see Table IA.1).
[9] We assume that personal bankruptcies are more consequential to individuals' financial status than foreclosures. First, in our sample, bankruptcies have a greater initial impact on individuals' credit scores than foreclosures. In addition, personal bankruptcies remain in credit records for ten years and foreclosures for seven years.
[10] A basic explanation on Chapter 7 Bankruptcy procedure is available on the website of the U.S Courts: https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-7-bankruptcy-basics.

outstanding mortgage debt, thereby forestalling or preventing the sale of their homes. Borrowers filing for Chapter 13 must satisfy the income and debt amount requirements for debt relief and must pay a discretionary amount to creditors based on a three- to five-year repayment plan.[11] An individual is eligible for filing for Chapter 13 Bankruptcy as long as the person's outstanding unsecured debts are less than $465,275 and secured debts are less than $1,395,875.[12] However, under Chapter 13, households enjoy much stronger protection from foreclosures (Lindblad, Quercia, Jacoby, Wang, and Zhao (2015)) because individuals can keep their property and pay their debts over time. Therefore, Chapter 13 provides an important backstop from foreclosure for financially distressed borrowers, allowing them to recover economically more quickly (Dobbie and Song (2015)).

We test the differential effect of Chapter 7 and Chapter 13 bankruptcy filings on the probability of divorce in Table 5. In Columns (1) and (3), the effect of Chapter 7 bankruptcy filings is not statistically significant, but the marginal effect of Chapter 13 bankruptcy filings is -0.48 percentage points, a 7% reduction in the probability of divorce relative to the unconditional mean (Column 2). In Column (4), we include additional measures for individual financial distress. Filing for bankruptcy through Chapter 13 decreases the probability of divorce by 0.58 percentage points, 8% of the unconditional mean. Importantly, foreclosures still have the biggest positive impact on the likelihood of divorce.

[Insert Table 5]

Overall, the analysis in this section provides additional evidence on how policies that protect housing stability affect households' ability to address financial distress and has important economic and social consequences.

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[11] If the individual's income is below the median of the state income, then the repayment plan should be for three years, and if it is above the median of the state income, it should be for five years.

[12] More details on Chapter 13 procedure are available on the website of the U.S Courts https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-13-bankruptcy-basics.

### 3.4. Event study analysis

A concern in our empirical specification is the possibility that individuals may act strategically around bankruptcy and foreclosure proceedings, and thus they may try to time their divorce to minimize the financial impact of pending foreclosures. In other words, anticipated divorces may predict current or past foreclosure activity. In addition, there are concerns that our differences-in-differences model in (1) may not adequately control for the differences between individuals who experience financial distress and those who do not. The potential violation in parallel trends is thus a potential impediment to our identification strategy.

Our identifying assumption is that absent from a significant financial distress event, the probability of filing for divorce should be equal across individuals. To evaluate whether this assumption holds, we modify our model using an event study, differences-in-differences regression. This framework also addresses, in part, recent criticism of two-way fixed effect differences-in-differences estimators (Goodman-Bacon (2021), and Callaway and Sant'Anna, (2021)). To this end, we estimate the following model:

$$Y_{i,m,t} = \alpha_{c,t} + \sum_{\tau} \delta_{\tau} D^{\tau}_{i,m} + \mathbf{X}_{i,t-1}\beta_t + \mathbf{C}_{m,t}\gamma_t + \epsilon_{i,m,t} \qquad (2)$$

In the above regression, $i$ refers to the individual, $m$ and $c$ refer to the census tract and county of the individual, and $t$ refers to the year. The vectors $\mathbf{X}_{i,t-1}$ and $\mathbf{C}$ include the same set of individual- and tract-level control variables as in equation (1). The variable $D^{\tau}$ is an indicator that equals one if year $t$ is $\tau$ years after individual $i$ goes through a *Foreclosure*, or *Chapter 13 Bankruptcy*.

Figure (1) illustrates the values of the $\delta\tau$ estimators for foreclosure. We also provide the results for Chapter 13 Bankruptcy in columns (2) of Table (6). The estimates of $\delta$ from equation (2) represent the change in the probability of divorce in year t due to a financial distress event in year $t - \tau$. The results are consistent with our previous findings. Because both foreclosures and divorces have lengthy proceedings, it is not surprising that there is a couple of years' difference between foreclosure and divorce. But importantly, we find no evidence that anticipated financial distress events are associated with changes in marital status.

## 4. Identification strategy: Natural disaster assistance and financial distress

We exploit plausibly exogenous variation in the probability of experiencing foreclosures around natural disasters to isolate the effects of financial strain on divorce rates from other confounding factors, such as personal characteristics or pre-existing financial conditions. The credit bureau data include individuals affected by a natural or declared disaster who receive assistance in the form of voluntary disaster-related credit reporting (Natural Disaster Relief). When a natural or declared disaster impacts a bank's communities, the Office of the Comptroller of the Currency (OCC) encourages banks to reassess the credit needs of the community where the banks' customers reside. These measures could include debt restructuring, adjusting payments, and expediting lending decisions when possible. However, the OCC only provides guidelines and does not mandate any particular action regarding consumers' debt relief.[13]

For some disaster-affected consumers, lenders may choose to apply disaster flags to certain credit report tradelines to temporarily mask negative tradeline-specific information that could otherwise adversely impact the consumers' VantageScores and reduce credit access (Guttman-Kenney, 2023). We hypothesize that the application of disaster flags reduces the probability of foreclosure driven by a natural disaster—a large, plausibly unexpected shock to household

[13] The OCC supervisory guidelines can be found in the following link: https://www.occ.gov/news-issuances/bulletins/2012/bulletin-2012-28.html

financial health. Therefore, the variation in foreclosure rates in our tests is driven by financially distressed individuals who avoid foreclosure because of the source of distress.

Our analysis uses an indicator on whether an individual has received assistance after a disaster as an instrumental variable. We identify approximately 138,000 instances in our sample of individuals tied to natural disaster assistance. Figure 2 illustrates the proportion of individuals affected by a natural disaster in our sample.[14] Approximately one-fifth of disaster-relief trades occurred in 2017 in Texas and Louisiana during Hurricane Harvey. However, excluding this year from the analysis does not alter our results. Figure 3 shows county-level maps that depict the cross-sectional and time series variation of the average rates of borrowers with at least one natural disaster relief trade in their credit reports.

### 4.1 Credit access during natural disaster relief

We first test whether Natural Disaster Relief predicts an improvement in credit access in the same year the borrower receives the flag in their credit report. This analysis is crucial to establish the effectiveness of the disaster relief program in providing financial support to affected individuals. Table 7 reports the results for different credit access outcomes.

The results in column (1) show that borrowers increase their credit card utilization by 48 percent and their indebtedness by 4 percent (column 2). Additionally, average credit card limits increase by 4% (column 3), and total debt balance rises by 10% (column 4). The increase in mortgage debt drives this effect, with an average increase of 20% (column 5). Credit card and auto debt also increase on average by 8% (column 6) and 3% (column 7), respectively. Furthermore, in Figure 4, we provide evidence that borrowers who receive a Natural Disaster Relief experience no change or a slight increase in their average credit score.

[14] The summary statistics of affected individuals in our sample match the information reported from a larger sample of the US population used in a report from the Consumer Financial Protection Bureau (CFPB): https://bit.ly/3uLdqbd

In contrast, individuals with a foreclosure event experience a decrease of 40 points on their credit score. This finding highlights the positive impact of the disaster relief program on the financial well-being of affected individuals, as it helps maintain their credit scores and access to credit.

[Insert Table 7]

**4.2 Natural disaster relief and foreclosure**

Having established the effectiveness of the Natural Disaster Relief program in providing financial support and maintaining credit access for affected individuals, we now examine its impact on foreclosure rates and the subsequent effect on divorce rates. We use the variation in foreclosure rates driven by disaster relief as an instrumental variable to isolate the causal effect of financial distress on divorce.

Table 8 presents the results of our analysis. In Column (1), we assess the validity of the instrument by regressing foreclosure on whether the individual has received natural disaster assistance. The first-stage regression estimates suggest that financially distressed individuals who receive natural disaster assistance are 20 basis points less likely to experience a foreclosure, approximately a 30% drop from the unconditional mean of foreclosure (0.67%). The F-statistic (KP Wald F-stat) is 44.5, which meets the Stock-Yogo weak identification criteria.

The results of the second-stage regression, presented in Column (2), reveal that individuals who experience foreclosure are approximately one percentage point more likely to divorce. This change represents approximately a 15% increase in the unconditional mean of divorce.

Our identifying assumption is that, after accounting for all controls and fixed effects in the model, natural disaster assistance affects households' divorce decisions only through its impact on foreclosure. Our regressions control for a host of household and local economic characteristics and restrictive, individual-level fixed effects that account for many unobservable attributes that may correlate with individuals' divorce decisions and natural disasters. The exogenous nature of the variation in foreclosure driven by the disaster relief program makes it more challenging to identify unobservable factors that decrease foreclosures and increase divorces. Finally, despite their large impact on foreclosure, we find no evidence that natural disaster assistance directly affects the probability of divorce, both unconditionally and when we exclude from our sample individuals who have not experienced a foreclosure.[15]

Overall, the instrumental variable analysis provides further corroborative evidence that financial distress is a statistically significant driver of marital instability and emphasizes the importance of housing security for personal welfare.

[Insert Table 8]

# 5. Robustness

## 5.1. Hazard models

We also examine the impact of financial distress on divorce using a Cox proportional hazard model. The study of marriage dissolution (i.e., marriage death) is a natural setting for hazard rate analysis. The hazard rate is defined as the probability an individual divorces at time $t$ conditional on being married up to $t$. The coefficient estimates of a Cox proportional hazard model are agnostic to the form of the baseline hazard function (Tibshirani (1982)).

$$h\,(t|X) = h_0\,(t) \exp\,\{\beta' X\} \qquad (3)$$

The first term, $h_0\,(t)$, which is the baseline hazard function, is unspecified. The regressors enter into the second term as $\exp\,\{\beta' X\}$. The hazard model contains the financial distress measure,

[15] We tabulate the results from these regressions in the Internet Appendix.

*Foreclosure Flag*, which is an indicator variable that equals one when the individual has experienced a foreclosure event in the current period or past periods and zero otherwise. The vector **X** also includes the same set of individual-level control variables as delineated in equation (1).

Table 9 shows that married individuals who experience foreclosure have higher divorce rates. In particular, there is a 16.6% increased risk for divorce among married individuals who experience or have experienced a foreclosure event relative to married individuals who have not (Column 1).[16] To mitigate concerns that the survival times between distinct individuals in the sample may not be independent (i.e., both partners appear in the sample), we implement a hazard model based on only females and find consistent results (Column 2).

[Insert Table 9]

In Figure 4, we alternatively plot the Kaplan-Meier estimates of the survival curves based on differences in foreclosure history. The survival curves estimate the probability an individual is still married *t* years after entering the sample. We restrict this analysis to married individuals in 2011 with mortgage debt. For each individual, we collapse multiple records into one record and assign treatment based on foreclosure occurrences. The treated group consists of married individuals who experienced a foreclosure in 2011, and the control group consists of married individuals who have not experienced a foreclosure during the sample period.[17] The relative steepness of the survival curves in Panel A suggests that divorce rates are greater among treated individuals and corroborates our previous findings. When we restrict our analysis to only females, we obtain similar results (Panel B).

[16] For this analysis, the sample is constructed by limiting observations to individuals who were married at some point from 2011-2019. The individual enters the sample during the first year the person is married. The last year of record for the individual is the earlier of (i) the year of first divorce (during 2011-2019) and (ii) the last year of observation if no divorce occurs. Standard errors are clustered at the individual level.
[17] The results are robust if we define the control group as married homeowners who did not foreclose in 2011.

[Insert Figure 4]

### 5.2. Local economic shocks and other non-linear models

Our results remain robust to several alternative empirical specifications. We first examine whether our results are driven by changes in local economic demand as reflected in the labor market. Extant literature examines the sensitivity of tradable and non-tradable industries to economic factors such as house prices and finds greater sensitivity among non-tradable employment to local shocks (Mian and Sufi (2014), Adelino, Schoar, and Severino (2015), and Giroud and Mueller (2017)). Firms in tradable industries sell products and services across regions or countries, whereas firms in non-tradable industries mainly serve local markets (Porter (2003)).

Consequently, we identify census tracts that have experienced large economic shocks on an annual basis by measuring whether there were large statistical changes between tradable employment growth and non-tradable employment growth. A significant change in tradable and non-tradable employment could indicate meaningful changes in the local economic environment. In Table 9, we include only the sample of individuals who lived in census tracts that did not experience substantial relative changes in tradable and non-tradable employment. We follow equation (1) and regress *Divorce* on our explanatory variables, *Foreclosure*, *Repossession*, *High Collections (Non-Med)*, *Being Delinquent*, and *Bankruptcy*. We note that foreclosures, debt in collections, and delinquencies remain statistically significant and meaningful predictors of future divorce, suggesting that our results are robust despite varying household exposures to economic conditions.

[Insert Table 10]

Our results also remain robust when we regress *Divorce* on explanatory variables of interest using logistic models. In Table IA.2, we find that the odds of divorce are 11%- 22%

higher for individuals experiencing financial distress (i.e., foreclosures, high debt in collections, and delinquencies). The findings in the logit models are qualitatively similar to the results from our baseline OLS estimates in Tables 3 and 4.

## 6. Discussion

Overall, we provide evidence on how individuals' financial distress affects their marital stability. Negative financial circumstances strongly predict the incidence of divorce. However, not all kinds of financial distress create equal stress in households. Delinquencies, high debt in collections, and foreclosures lead to increased rates of divorce. Even though bankruptcy and foreclosure are indicators of severe financial distress for individuals, they have diametrically different effects on the probability of divorce. Households that go through foreclosure are 0.53 percentage points more likely to become divorced, an 8% increase from the unconditional probability of divorce, whereas Chapter 13 bankruptcies, which protect debtors from foreclosure, have the opposite impact. The effects of foreclosure and bankruptcy protection on household stability are distinct from health- or employment-related shocks. Our findings highlight the role of financial stability and housing security as a determinant of family structure, suggesting that households' financial distress has broader social consequences.

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## Variable Definitions

| Variable | Description |
|---|---|
| Divorce | Variable that equals one hundred when an individual changes their marital status from married to single, and zero otherwise. |
| Financial Distress Event | Indicator variable that equals one when an individual has one of the following events in their credit history in a given year: bankruptcy, foreclosure, or lagged repossession, and zero otherwise. |
| Bankruptcy | Indicator variable that equals one when an individual had a bankruptcy filing in the last 12 months, and zero otherwise |
| Foreclosure | Indicator variable that equals one when an individual had a foreclosure in the last 12 months, and zero otherwise |
| Repossession | Indicator variable that equals one when an individual had an auto repossession in the last 12 months, and zero otherwise |
| Being Delinquent | Indicator variable that equals one when an individual is delinquent on any credit product for 30 days or more in the last 12 months, and zero otherwise |
| High Collections (Med) | Indicator variable that equals one when an individual's medical debt in collections is in the top tercile of the annual distribution of positive medical debt in collections, and zero otherwise. |
| High Collections (Non-Med) | Indicator variable that equals one when an individual's non-medical debt in collections is in the top tercile of the annual distribution of positive non-medical debt in collections, and zero otherwise. |
| Credit score | A discrete variable of the individual's credit score ranging from 505 to 850 in increments of 10 points. |
| Homeowner | Indicator variable that equals one when the individual has an open mortgage in the last 12 months, and zero otherwise. |
| Age | The Individual's age. |
| Female | Indicator variable that equals one if the individual's gender is female, and zero otherwise. |
| Log(Household Income) | The natural logarithm of the household estimated income in thousands of dollars. |
| Log(Household Income)$^2$ | The squared of the natural logarithm of the household estimated income in thousands of dollars. |
| Poverty Rate | Poverty rate of individuals 18-64yo at the census tract level. |
| Log(Population Density) | The natural logarithm of population density at the census tract level |
| Minority Share | The proportion of non-white individuals living in a census tract |
| Average Household Size | The average number of individuals in a household at the census tract level |
| Percent HS Diploma | The proportion of individuals with high school diplomas in a census tract |
| Percent Govt. Employment | The proportion of individuals employed by the government in a census tract |
| Percent w/ Children | The proportion of households with children in a census tract |
| Natural Disaster Assistance | An individual that the credit bureau indicates has at least one credit product affected by a declared natural disaster |

**Figure 1:** Dynamic Treatment Effects

This figure shows the differences-in-differences estimation results of equation 2. These estimates represent the change in the probability of divorce in year $t$ due to the event of foreclosure in year $t-\tau$. For example, the point estimate for t+1 is the change in probability of divorce in year t due to a foreclosure occurring at t-1.

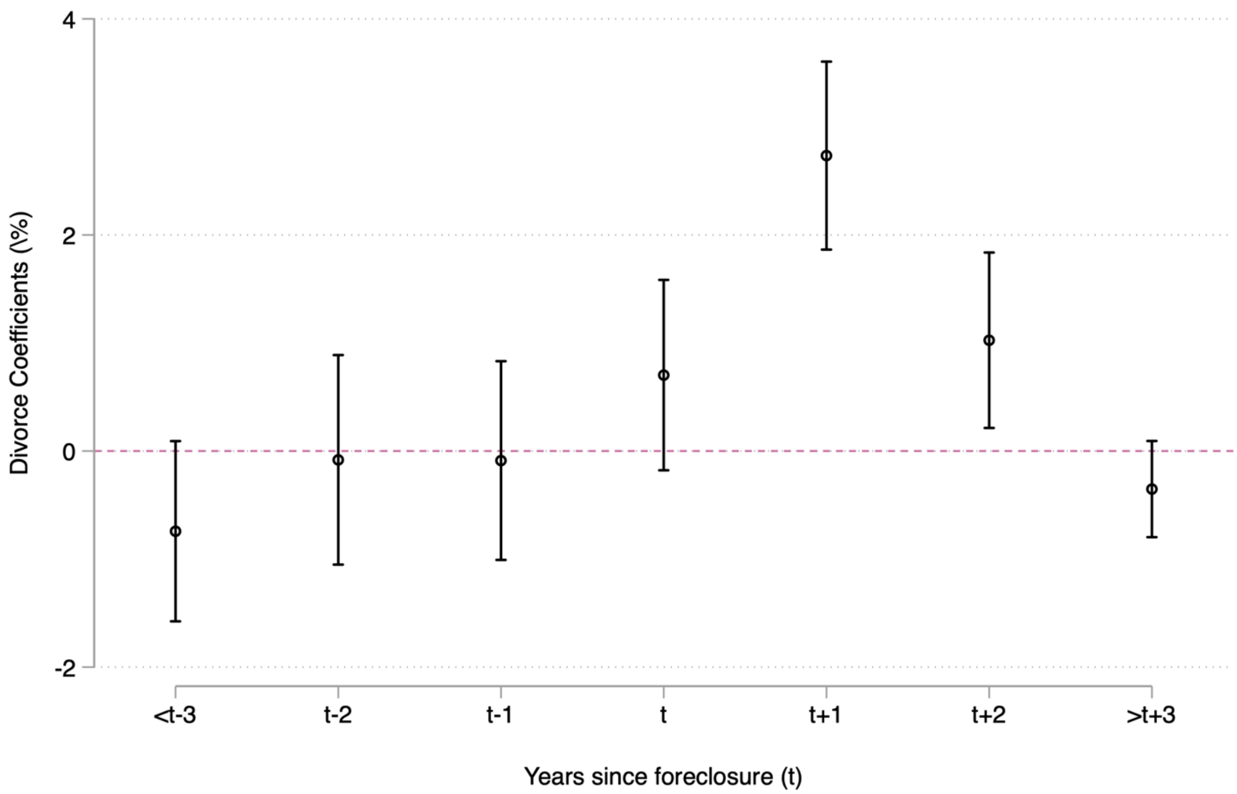


**Figure 2:** Natural Disaster Assistance

This figure shows the proportion of individuals that the credit bureau reports with at least one natural-disaster-relief trade during the sample period 2011-2019.

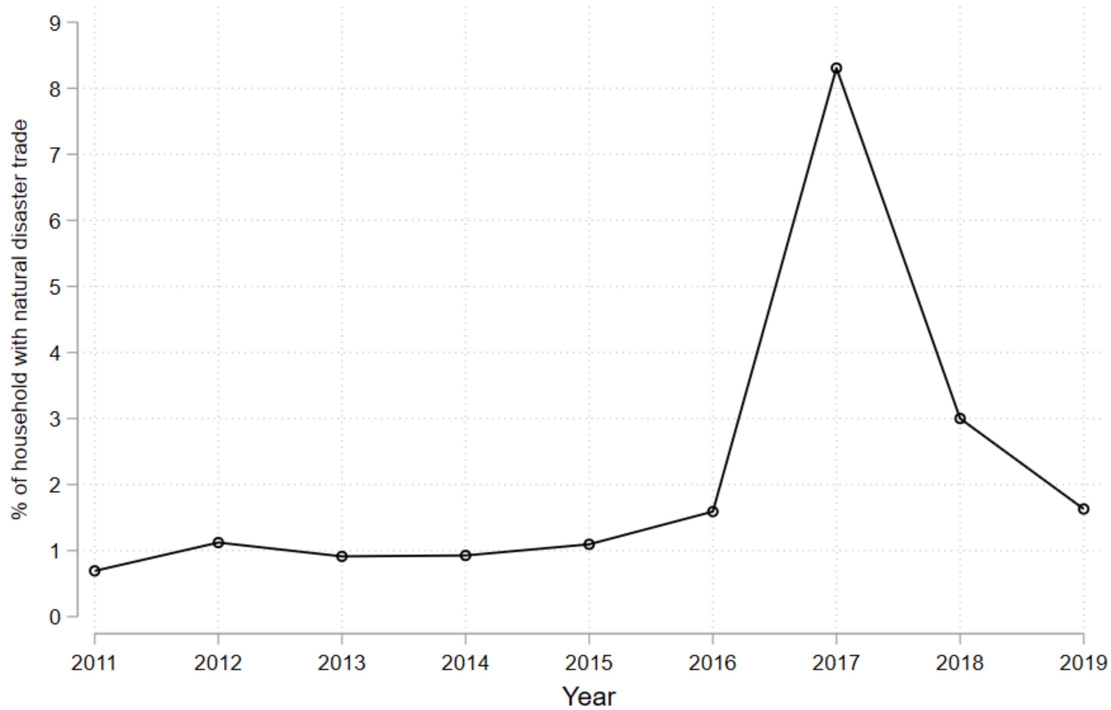


**Figure 3:** Geographic and Time Series Variation on the Natural Disaster Flag

These figures map the geographic distribution of the proportion of individuals the credit bureau reports with at least one natural disaster relief trade in each county for some years of the sample.

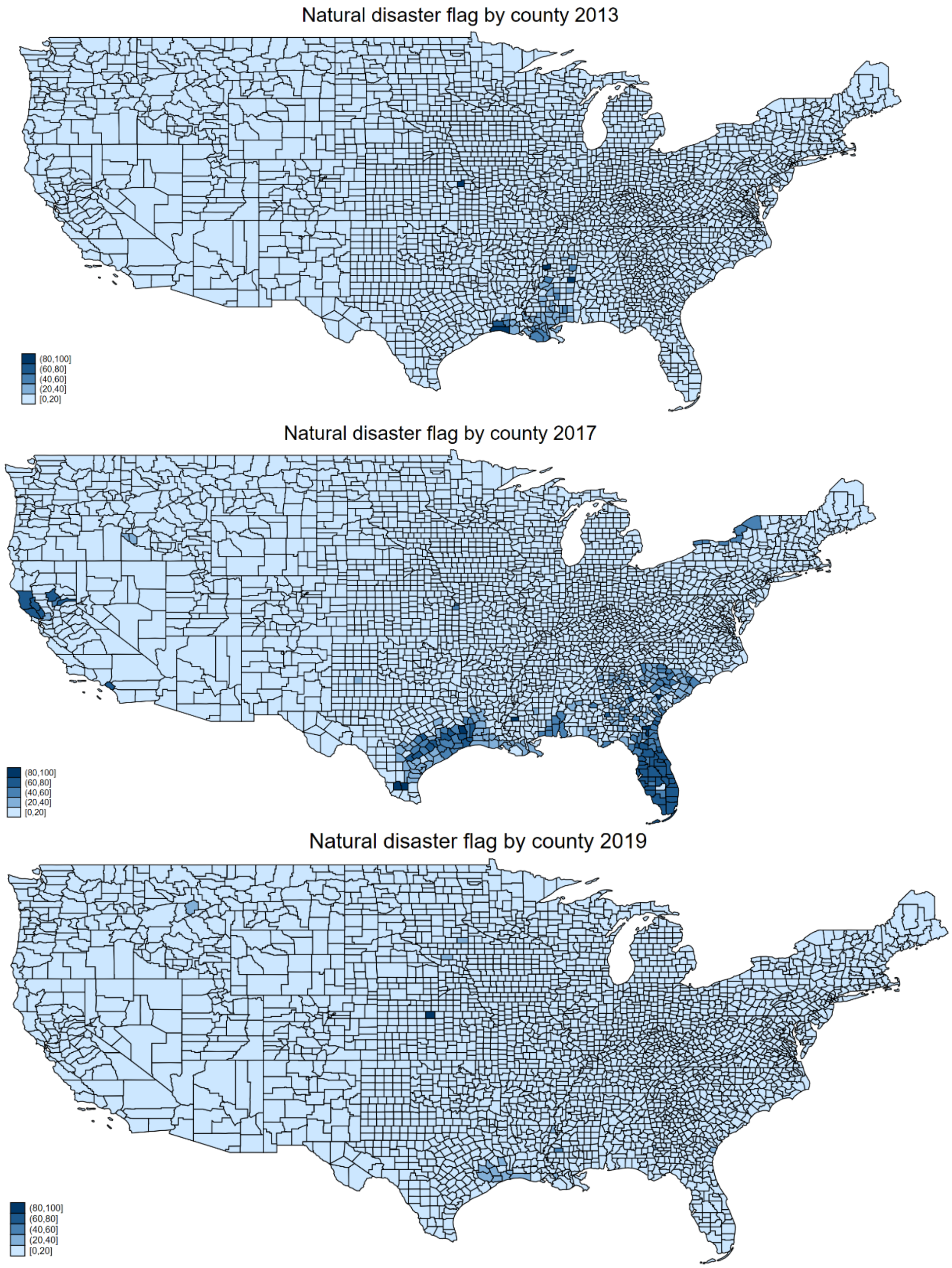


**Figure 4:** Credit Access and Credit Score Impact After Natural Disaster Relief

This figure shows the average impact on credit access and credit score when borrowers receive a natural disaster relief flag on their credit report. Panel A displays the percentage increases of different credit access outcomes. *Credit Card Utilization* measures the outstanding credit card debt ratio relative to total credit card limits. *Indebtedness* is the borrower's estimated debt-to-income ratio. *Credit Card Limit* is the total credit card limit that the borrower has available. *Total Debt, Mortgage Debt, Credit Card Debt,* and *Auto Debt* are the end-of-year balance of outstanding debt in each category, respectively. Panel B compares the average change in credit score when borrowers receive a natural disaster relief flag versus a foreclosure event.

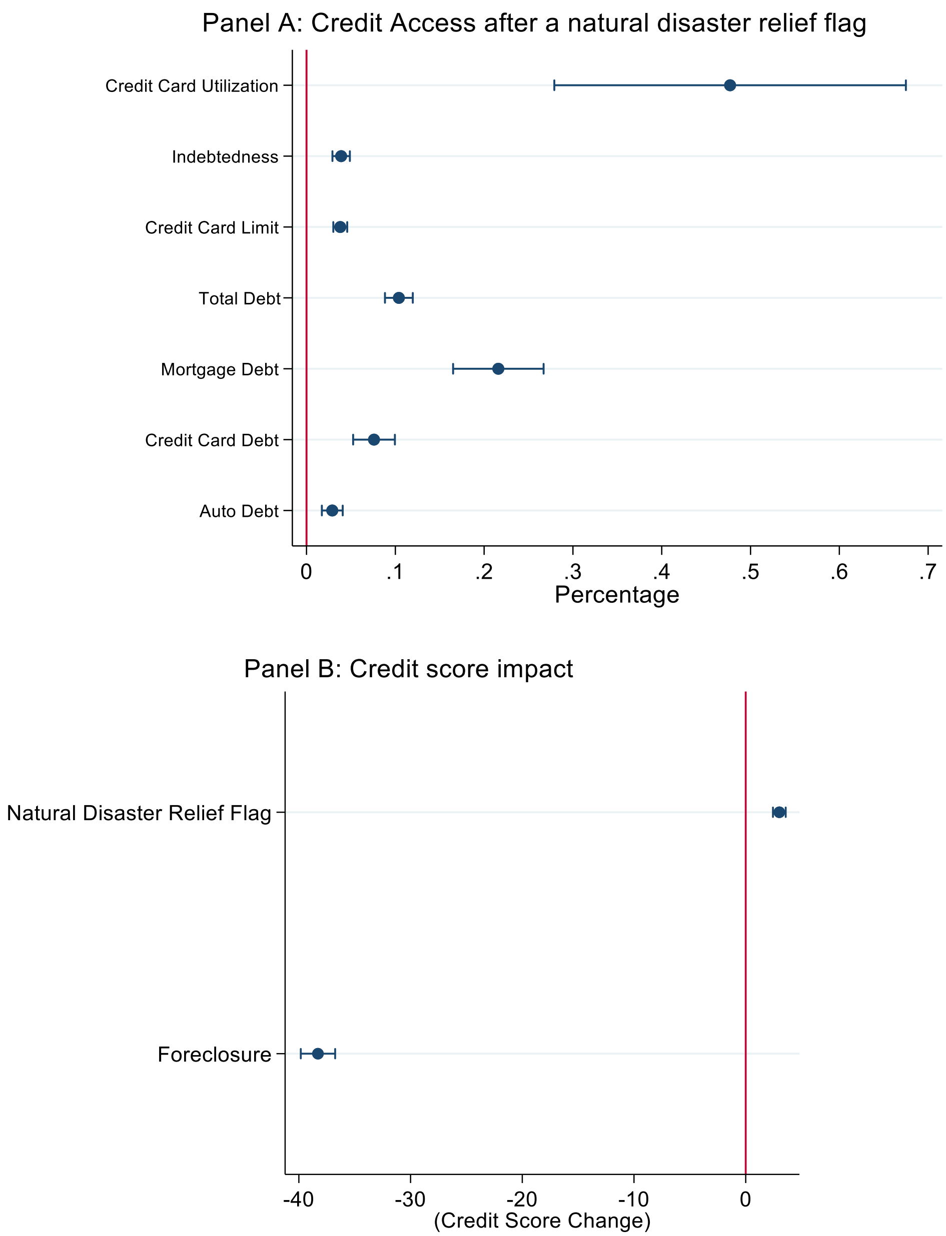
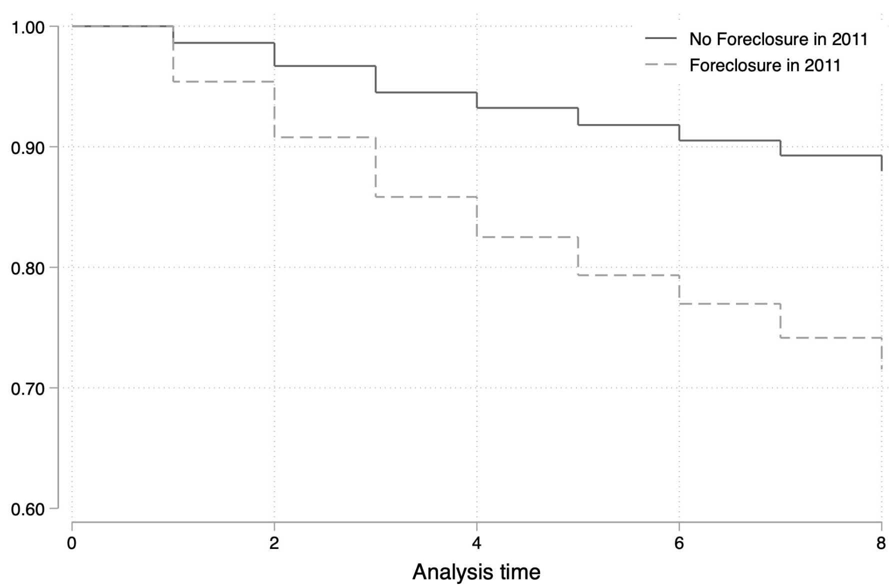


**Figure 5:** Kaplan-Meier Estimates

This figure shows the estimated survival function for two groups of individuals. We restrict this analysis to married individuals in 2011 with mortgage debt. For each individual, we collapse multiple records per individual into one record and assign treatment based on foreclosure occurrences. The treated group consists of married individuals who experienced a foreclosure in 2011, and the control group consists of married individuals who have not experienced a foreclosure during the sample period. The solid line represents the estimated survivor function of the control group. The dotted line represents the estimated survivor function of the treated group. Panel A includes all eligible individuals, whereas Panel B only includes females.

*Panel A: All Individuals*




*Panel B: Female Only*

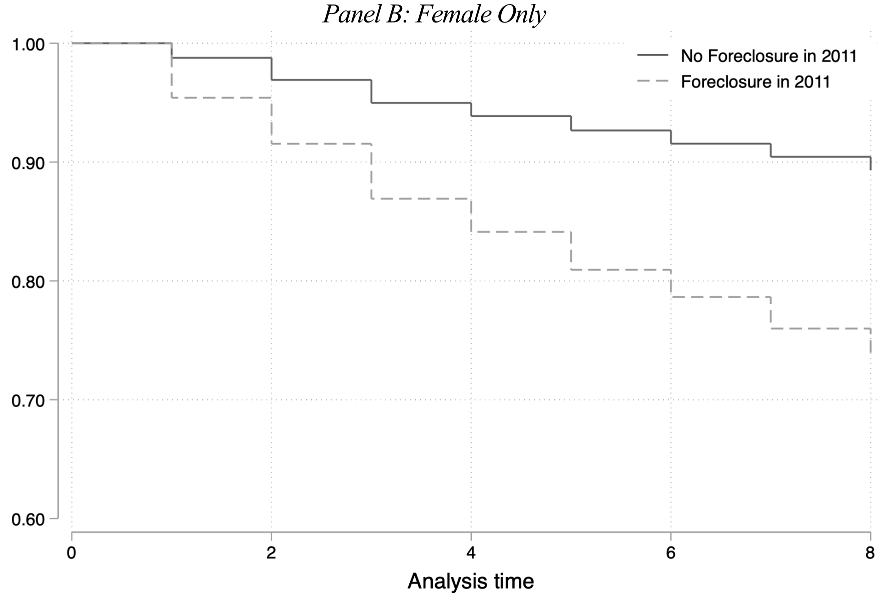


**Table 1:** Summary Statistics

This table presents summary statistics for a 1% representative national sample of individual credit bureau records. The final sample includes approximately 2.0 million individuals from 2011-2019. *Divorce* is the annual rate of change of marital status from married to single. *Credit Score* is the individual credit score. *Estimated Income* is the household estimated income in thousands of dollars. *Male* is the proportion of individuals whose gender is reported as male. *Age* is the individual's age. The variables related to individual financial conditions are the following: *Total Debt* is the total balance on the individual's debt in thousands of dollars. *Mortgage Debt*, *Auto Debt*, and *Credit Card Debt* are the individual's balances in those debt categories in thousands of dollars. *Financial Distress Event* is the percentage of individuals in each year who experience either a bankruptcy, foreclosure, and/or lagged repossession. *Foreclosure* indicates whether the individual experiences foreclosure. *Being Delinquent* is the percentage of individuals who are at least 30 days delinquent in the last 12 months. *Have Debt in Collections* is the percentage of individuals with debt in collections. *Non-Medical Debt in Collections (>0)* is the individual's balance of non-medical debt in collections in thousands of dollars, conditional on the individual having positive non-medical debt in collections. *Medical Debt in Collections (>0)* is the individual's balance of medical debt in collections in thousands of dollars, conditional on the individual having positive medical debt in collections. *Credit Card Utilization* is the percentage of an individual's credit card limit that has been drawn. *Natural Disaster-Relief* indicates whether an individual has at least one credit account that the credit bureau has indicated as affected by a natural disaster.

| | N | Mean | SD | P10 | P50 | P90 |
|---|---|---|---|---|---|---|
| Divorce (%) | 9,189,581 | 6.8 | 25.1 | 0.0 | 0.0 | 0.0 |
| Credit Score | 9,189,581 | 699.9 | 104.3 | 536.0 | 720.0 | 818.0 |
| Estimated Income ($1,000) | 9,189,581 | 98.2 | 64.9 | 36.0 | 79.0 | 196.0 |
| Male (%) | 9,189,581 | 52.6 | 49.9 | 0.0 | 100.0 | 100.0 |
| Age | 9,189,581 | 51.5 | 16.6 | 30.0 | 51.0 | 74.0 |
| Credit Card Debt ($1,000) | 9,189,581 | 4.4 | 7.8 | 0.0 | 1.0 | 13.3 |
| Mortgage Debt ($1,000) | 9,189,581 | 76.1 | 132.1 | 0.0 | 0.0 | 252.6 |
| Financial Distress Event (%) | 9,189,581 | 1.0 | 10.0 | 0.0 | 0.0 | 0.0 |
| Foreclosure (%) | 9,189,581 | 0.39 | 6.2 | 0.0 | 0.0 | 0.0 |
| Ch 13 Bankruptcy (%) | 9,189,581 | 0.16 | 4.0 | 0.0 | 0.0 | 0.0 |
| Ch 7 Bankruptcy (%) | 9,189,581 | 0.29 | 5.4 | 0.0 | 0.0 | 0.0 |
| Natural Disaster Relief (%) | 9,189,581 | 1.5 | 12.2 | 0.0 | 0.0 | 0.0 |
| Being Delinquent (%) | 9,189,581 | 17.4 | 37.9 | 0.0 | 0.0 | 100.0 |
| Have Debt in Collections (%) | 9,189,581 | 22.7 | 41.9 | 0.0 | 0.0 | 100.0 |
| Non-Medical Debt in Collections (>0) ($1,000) | 1,747,287 | 2.0 | 3.9 | 0.0 | 0.6 | 5.3 |
| Medical Debt in Collections (>0) ($1,000) | 1,331,777 | 2.0 | 4.0 | 0.1 | 0.7 | 4.7 |
| Credit Card Utilization (%) | 6,622,304 | 30.7 | 33.8 | 0.4 | 14.4 | 91.7 |
| Poverty Rate (%) | 9,189,581 | 11.2 | 8.4 | 2.8 | 9.0 | 22.6 |
| County Population Density | 9,189,581 | 1,514.5 | 3,910.8 | 56.9 | 510.3 | 2,726.6 |
| Minority Share (%) | 9,189,581 | 21.7 | 20.6 | 3.0 | 14.8 | 51.7 |
| Household Size | 9,189,581 | 2.7 | 0.5 | 2.2 | 2.7 | 3.3 |
| Percent HS Diploma (%) | 9,189,581 | 88.3 | 9.8 | 75.5 | 91.1 | 97.4 |
| Percent Govt. Employed (%) | 9,189,581 | 4.8 | 3.5 | 1.4 | 4.0 | 9.2 |
| Percent w/ Children (%) | 9,189,581 | 33.7 | 10.6 | 21.4 | 32.7 | 47.8 |
| ZIP Code Home Median Prices ($1,000) | 9,189,581 | 262.7 | 204.8 | 93.8 | 200.9 | 498.4 |
| Unemployment Rate (%) | 9,189,581 | 5.7 | 2.4 | 3.2 | 5.2 | 9.2 |

**Table 2:** Univariate Differences

This table shows the mean of the variables reported in the summary statistics section for different groups of the sample. Column (1) reports the mean for the group of individuals who did not experience a divorce in a given year. Column (2) reports the mean for the group of individuals who experienced a divorce in a given year. Column (3) shows a t-test for the mean difference between Columns (1) and (2). Column (4) No Fin. Distress shows the variable means for individuals who did not experience either a bankruptcy, foreclosure, or lagged repossession in a given year. Column (5) Fin. Distress shows the variable means for individuals who experienced either a bankruptcy, foreclosure, and/or lagged repossession in a given year. Column (6) shows a t-test for the mean difference between Columns (4) and (5). *Credit Score* is the individual credit score. *Estimated Income* is the household estimated income in thousands of dollars. *Male* is the proportion of individuals whose gender is reported as male. *Age* is the individual's age. *Total Debt* is the total balance on the individual's debt in thousands of dollars. *Mortgage Debt*, *Auto Debt*, and *Credit Card Debt* are the individual's balances in those debt categories in thousands of dollars. *Being Delinquent* is the percentage of individuals who are at least 30 days delinquent in the last 12 months. *Have Debt in Collections* is the percentage of individuals with debt in collections. *Non-Medical Debt in Collections (>0)* is the individual's balance of non-medical debt in collections in thousands of dollars, conditional on the individual having positive non-medical debt in collections. *Credit Card Utilization* is the percentage of an individual's credit card limit that has been drawn. Divorce is the percentage of individuals who changed their marital status from married to single. In this analysis, we limit our observations to individuals who are married in the prior period.

| | (1)<br>No Divorce | (2)<br>Divorced | (3)<br>1-2 | (4)<br>Fin.Distress=0 | (5)<br>Fin.Distress=1 | (6)<br>4-5 |
|---|---|---|---|---|---|---|
| Credit Score | 704.74 | 633.07 | 71.68*** | 701.22 | 571.97 | 129.24*** |
| Estimated Income ($1,000) | 100.73 | 63.02 | 37.71*** | 98.55 | 62.12 | 36.44*** |
| Male (%) | 52.70 | 51.39 | 1.31*** | 52.59 | 54.84 | -2.25*** |
| Age | 52.19 | 41.33 | 10.86*** | 51.50 | 46.78 | 4.73*** |
| Total Debt ($1,000) | 97.05 | 44.75 | 52.30*** | 94.01 | 45.34 | 48.67*** |
| Auto Debt ($1,000) | 6.14 | 4.71 | 1.44*** | 6.06 | 4.36 | 1.71*** |
| Credit Card Debt ($1,000) | 4.55 | 2.54 | 2.01*** | 4.44 | 1.36 | 3.08*** |
| Mortgage Debt ($1,000) | 79.37 | 30.83 | 48.54*** | 76.51 | 34.63 | 41.88*** |
| Being Delinquent (%) | 16.78 | 26.42 | -9.63*** | 16.75 | 84.35 | -67.60*** |
| Have Debt in Collections (%) | 21.24 | 43.50 | -22.26*** | 22.50 | 46.75 | -24.25*** |
| Non-Medical Debt in Collections (>0) ($1,000) | 2.02 | 2.13 | -0.11*** | 2.00 | 3.43 | -1.43*** |
| Credit Card Utilization (%) | 30.06 | 42.11 | -12.05*** | 30.54 | 59.95 | -29.41*** |
| Divorce (%) | | | | 6.72 | 9.76 | -3.03*** |

**Table 3:** Financial Distress and Divorce

The outcome variable, *Divorce*, equals one hundred when the individual changes their marital status from married to single and zero otherwise. *Financial Distress Event* is an indicator variable that equals one when the individual has one of the following events in their credit history in a given year: bankruptcy, foreclosure, or lagged repossession, and zero otherwise. The following variables are lagged: *High Collections (Med)*, *Credit score bins)*, *Homeowner*, *Log(Estimated Income)*, and *Log(Estimated Income)*$^2$. In this analysis, we limit our observations to individuals who are married in the prior period. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| Financial Distress Event | 0.318*** | 0.325*** | 0.281*** |
| | (0.105) | (0.109) | (0.108) |
| High Collections (Med) | 0.740*** | 0.722*** | 0.653*** |
| | (0.082) | (0.082) | (0.084) |
| Credit score | -0.003*** | -0.003*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) |
| Homeowner | -1.415*** | -1.397*** | -1.194*** |
| | (0.042) | (0.041) | (0.040) |
| Log(Estimated Income) | 7.452*** | 7.207*** | 6.434*** |
| | (0.516) | (0.483) | (0.448) |
| Log(Estimated Income)$^2$ | -0.831*** | -0.804*** | -0.717*** |
| | (0.055) | (0.051) | (0.047) |
| Age | -0.012* | -0.012* | -0.008 |
| | (0.007) | (0.007) | (0.007) |
| Poverty Rate (%) | 0.344*** | 0.354*** | |
| | (0.010) | (0.010) | |
| Log(Population Density) | 2.624*** | 2.186*** | |
| | (0.088) | (0.083) | |
| Minority Share (%) | 0.156*** | 0.150*** | |
| | (0.007) | (0.008) | |
| Household Size | -8.838*** | -9.439*** | |
| | (0.387) | (0.408) | |
| Percent HS Diploma (%) | -0.047*** | -0.075*** | |
| | (0.012) | (0.011) | |
| Percent Govt. Employed (%) | -0.109*** | -0.102*** | |
| | (0.013) | (0.008) | |
| Percent w/ Children (%) | -0.075*** | -0.052*** | |
| | (0.010) | (0.009) | |
| Year FE | Yes | No | No |
| Individual FE | Yes | Yes | Yes |
| County × Year FE | No | Yes | No |
| Tract × Year FE | No | No | Yes |
| Observations | 8,842,969 | 8,842,661 | 8,820,930 |
| Adjusted $R^2$ | 0.259 | 0.263 | 0.322 |

**Table 4:** Financial Distress Types and Divorce

The outcome variable, *Divorce*, equals one hundred when the individual changes their marital status from married to single and zero otherwise. *Foreclosure* is an indicator variable that equals one when an individual had a foreclosure in the last 12 months, and zero otherwise. *Repossession* is an indicator variable that equals one when an individual had an auto repossession in the last 12 months, and zero otherwise. *High Collections (Non-Med)* is an indicator variable that equals one when the individual is in the top tercile of the distribution of non-medical debt in collections, and zero otherwise. *Being Delinquent* is an indicator variable that equals one when an individual is delinquent on any credit product for 30 days or more in the last 12 months, and zero otherwise. *Bankruptcy* is an indicator variable that equals one when an individual had a bankruptcy filing in the last 12 months, and zero otherwise. The following variables are lagged: *Repossession*, *High Collections (Non-Med)*, *Being Delinquent*, *High Collections (Med)*, *Credit score bins)*, *Homeowner*, *Log(Estimated Income)*, and *Log(Estimated Income)*$^2$. In this analysis we limit our observations to individuals who are married in the prior period. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Foreclosure | 0.500*** | | | | | 0.421*** |
| | (0.161) | | | | | (0.161) |
| Repossession | | 0.430 | | | | 0.276 |
| | | (0.301) | | | | (0.300) |
| High Collections (Non-Med) | | | 0.392*** | | | 0.383*** |
| | | | (0.067) | | | (0.067) |
| Being Delinquent | | | | 0.346*** | | 0.336*** |
| | | | | (0.034) | | (0.034) |
| Bankruptcy | | | | | 0.050 | -0.074 |
| | | | | | (0.129) | (0.130) |
| High Collections (Med) | 0.743*** | 0.742*** | 0.748*** | 0.745*** | 0.742*** | 0.751*** |
| | (0.082) | (0.082) | (0.082) | (0.082) | (0.082) | (0.082) |
| Credit score | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Homeowner | -1.413*** | -1.407*** | -1.405*** | -1.420*** | -1.407*** | -1.423*** |
| | (0.042) | (0.042) | (0.042) | (0.042) | (0.042) | (0.042) |
| Log(Estimated Income) | 7.447*** | 7.454*** | 7.446*** | 7.520*** | 7.452*** | 7.511*** |
| | (0.516) | (0.516) | (0.516) | (0.516) | (0.516) | (0.516) |
| Log(Estimated Income)$^2$ | -0.830*** | -0.831*** | -0.830*** | -0.837*** | -0.831*** | -0.836*** |
| | (0.055) | (0.055) | (0.055) | (0.055) | (0.055) | (0.055) |
| Age | -0.012* | -0.012* | -0.012* | -0.012* | -0.012* | -0.012* |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Poverty Rate (%) | 0.344*** | 0.344*** | 0.344*** | 0.344*** | 0.344*** | 0.344*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Log(Population Density) | 2.624*** | 2.624*** | 2.624*** | 2.623*** | 2.624*** | 2.623*** |
| | (0.088) | (0.088) | (0.088) | (0.088) | (0.088) | (0.088) |
| Minority Share (%) | 0.156*** | 0.156*** | 0.156*** | 0.156*** | 0.156*** | 0.156*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Household Size | -8.838*** | -8.838*** | -8.837*** | -8.835*** | -8.838*** | -8.833*** |
| | (0.387) | (0.387) | (0.387) | (0.387) | (0.387) | (0.387) |
| Percent HS Diploma (%) | -0.047*** | -0.047*** | -0.047*** | -0.047*** | -0.047*** | -0.047*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Percent Govt. Employed (%) | -0.109*** | -0.109*** | -0.109*** | -0.109*** | -0.109*** | -0.109*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Percent w/ Children (%) | -0.075*** | -0.075*** | -0.075*** | -0.075*** | -0.075*** | -0.075*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,842,969 | 8,842,969 | 8,842,969 | 8,842,969 | 8,842,969 | 8,842,969 |
| Adjusted $R^2$ | 0.259 | 0.259 | 0.259 | 0.260 | 0.259 | 0.260 |

**Table 5:** Chapter 7 vs. Chapter 13 Bankruptcy and Divorce

The outcome variable, *Divorce*, is a variable that equals one hundred when the individual changes their marital status from married to single and zero otherwise. *Chapter 7 Bankruptcy* and *Chapter 13 Bankruptcy* are indicator variables that equal one when an individual experiences a Chapter 7 and 13 bankruptcy in the last 12 months, respectively, and zero otherwise. *Foreclosure* is an indicator variable that equals one when the individual has a foreclosure event in their credit history in the last 12 months, and zero otherwise. In this analysis, we limit our observations to individuals who are married in the prior period. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ch 7 Bankruptcy | 0.306* | | 0.305* | 0.168 |
| | (0.172) | | (0.172) | (0.172) |
| Ch 13 Bankruptcy | | -0.483** | -0.482** | -0.581*** |
| | | (0.199) | (0.199) | (0.201) |
| Foreclosure | | | | 0.424*** |
| | | | | (0.161) |
| Repossession | | | | 0.274 |
| | | | | (0.299) |
| High Collections (Non-Med) | | | | 0.381*** |
| | | | | (0.067) |
| Being Delinquent | | | | 0.336*** |
| | | | | (0.034) |
| High Collections (Med) | 0.740*** | 0.743*** | 0.741*** | 0.750*** |
| | (0.082) | (0.082) | (0.082) | (0.082) |
| Credit score | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Homeowner | -1.409*** | -1.404*** | -1.407*** | -1.423*** |
| | (0.042) | (0.042) | (0.042) | (0.042) |
| Log(Estimated Income) | 7.454*** | 7.455*** | 7.458*** | 7.516*** |
| | (0.516) | (0.516) | (0.516) | (0.516) |
| Log(Estimated Income)$^2$ | -0.831*** | -0.831*** | -0.831*** | -0.837*** |
| | (0.055) | (0.055) | (0.055) | (0.055) |
| Age | -0.012* | -0.012* | -0.012* | -0.012* |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Poverty Rate (%) | 0.344*** | 0.344*** | 0.344*** | 0.344*** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Log(Population Density) | 2.624*** | 2.624*** | 2.624*** | 2.623*** |
| | (0.088) | (0.088) | (0.088) | (0.088) |
| Minority Share (%) | 0.156*** | 0.156*** | 0.156*** | 0.156*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Household Size | -8.838*** | -8.838*** | -8.838*** | -8.833*** |
| | (0.387) | (0.387) | (0.387) | (0.387) |
| Percent HS Diploma (%) | -0.047*** | -0.047*** | -0.047*** | -0.047*** |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| Percent Govt. Employed (%) | -0.109*** | -0.109*** | -0.109*** | -0.109*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Percent w/ Children (%) | -0.075*** | -0.075*** | -0.075*** | -0.075*** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Year FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Observations | 8,842,969 | 8,842,969 | 8,842,969 | 8,842,969 |
| Adjusted $R^2$ | 0.259 | 0.259 | 0.259 | 0.260 |

**Table 6:** Differences in Differences - Event Study

The estimates represent the effect of a financial distress event in year $t-\tau$ , ($\tau \in [-3, +3]$ or $\tau > t + 3$) on the probability of getting a divorce in year t using the following specification:

$$Y_{i,m,t} = \alpha_{c,t} + \sum_{\tau} \delta_{\tau} D_{i,m}^{\tau} + \mathbf{X}_{i,t-1}\beta_t + \mathbf{C}_{m,t}\gamma_t + \epsilon_{i,m,t} \qquad (2)$$

In the above regression equation, *i* refers to the individual, *m* and *c* refer to the census tract and county of the individual, and *t* refers to the year. **X** is a vector of individual-level controls (e.g., age, natural logarithm of household income and credit score, and homeownership indicator) that correlate with the probability of divorce and financial stress. **C** is a vector of tract-level controls that capture different aspects of individuals' local economic environment and includes the following variables: poverty rate, natural log of population density, minority share, average household size, as well as the proportion of households with children, with high school diploma, and with government employees. The variable $D^{\tau}$ is an indicator that equals one if year *t* is $\tau$ years after individual *i* goes through a *Foreclosure*, or Chapter 13 Bankruptcy. All regressions include county×year fixed effects. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | Foreclosure | Chapter 13 Bankruptcy |
|---|---|---|
| $\delta \leq t-3$ | -0.352 | -1.734*** |
| | (0.227) | (0.215) |
| $\delta = t-2$ | 1.025** | -1.210*** |
| | (0.414) | (0.371) |
| $\delta = t-1$ | 2.734*** | -1.013** |
| | (0.444) | (0.404) |
| $\delta = t$ | 0.703 | -0.959** |
| | (0.449) | (0.434) |
| $\delta = t+1$ | -0.088 | -0.672 |
| | (0.469) | (0.429) |
| $\delta = t+2$ | -0.082 | -0.391 |
| | (0.495) | (0.454) |
| $\delta \geq t+3$ | -0.742* | -0.483 |
| | (0.425) | (0.332) |
| County × Year FE | Yes | Yes |
| Observations | 1154676 | 1901898 |
| Adjusted $R^2$ | 0.038 | 0.036 |

**Table 7:** Natural Disaster Relief and Credit Access

This table shows the effects of a natural disaster relief flag on credit access outcomes. *Natural Disaster Assistance* is an indicator variable that equals one if the credit bureau has indicated the individual has at least one natural disaster relief trade and zero otherwise. The outcome variable in column 1, *Credit Card Utilization*, is the ratio of total credit card balances over the total credit card limit. In column 2, *Indebtedness* is the estimated average debt-to-income ratio. In Column 3, *Ln (Total Credit Card Limit)* is the natural logarithm of the sum of all the credit card limits. In Columns 4-7, *Ln(Total Debt)*, *Ln(Mortgage Debt)*, *Ln(Credit Card Debt)*, and *Ln(Auto Debt)* are the natural logarithm of the end-of-year debt balance in each category, respectively.

| | (1) Credit Card Utilization | (2) Indebtedness | (3) Ln(Total Credit Card Limit) | (4) Ln(Total Debt) | (6) Ln(Mortgage Debt) | (5) Ln(Credit Card Debt) | (7) Ln(Auto Debt) |
|---|---|---|---|---|---|---|---|
| Natural Disaster Assistance | 0.477$^{***}$ | 0.039$^{***}$ | 0.038$^{***}$ | 0.104$^{***}$ | 0.216$^{***}$ | 0.076$^{***}$ | 0.029$^{***}$ |
| | (0.101) | (0.005) | (0.004) | (0.008) | (0.026) | (0.012) | (0.006) |
| Credit Score Bins | -0.211$^{***}$ | -0.003$^{***}$ | 0.002$^{***}$ | -0.001$^{***}$ | -0.002$^{***}$ | -0.007$^{***}$ | 0.000$^{***}$ |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Log(Estimated Income) | 27.044$^{***}$ | -0.905$^{***}$ | 2.783$^{***}$ | 0.453$^{***}$ | 0.050 | 6.236$^{***}$ | 1.489$^{***}$ |
| | (1.406) | (0.045) | (0.047) | (0.092) | (0.202) | (0.156) | (0.065) |
| Log(Estimated Income)$^2$ | -2.437$^{***}$ | 0.048$^{***}$ | -0.254$^{***}$ | -0.035$^{***}$ | -0.012 | -0.575$^{***}$ | -0.121$^{***}$ |
| | (0.144) | (0.005) | (0.005) | (0.010) | (0.022) | (0.016) | (0.007) |
| Age | -0.030$^{**}$ | -0.001 | -0.001$^{***}$ | -0.002$^{**}$ | -0.004$^{**}$ | -0.004$^{***}$ | -0.003$^{***}$ |
| | (0.012) | (0.000) | (0.000) | (0.001) | (0.002) | (0.001) | (0.001) |
| Poverty Rate (%) | -0.007 | -0.003$^{***}$ | -0.001$^{***}$ | -0.005$^{***}$ | -0.011$^{***}$ | -0.002$^{***}$ | -0.001$^{***}$ |
| | (0.006) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) |
| Log(Population Density) | -0.116$^{***}$ | -0.030$^{***}$ | -0.008$^{***}$ | -0.028$^{***}$ | -0.042$^{***}$ | -0.021$^{***}$ | -0.005$^{***}$ |
| | (0.041) | (0.002) | (0.002) | (0.003) | (0.007) | (0.005) | (0.002) |
| Minority Share (%) | -0.007$^{***}$ | -0.002$^{***}$ | | | | | |
| | (0.003) | (0.000) | -0.000$^{***}$ | -0.001$^{***}$ | -0.003$^{***}$ | -0.001$^{***}$ | -0.000 |
| Household Size | 0.357$^{***}$ | 0.082$^{***}$ | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) |
| | (0.137) | (0.006) | 0.028$^{***}$ | 0.136$^{***}$ | 0.399$^{***}$ | 0.070$^{***}$ | 0.015$^{*}$ |
| Percent HS Diploma (%) | -0.002 | 0.003$^{***}$ | (0.005) | (0.010) | (0.024) | (0.016) | (0.008) |
| | (0.007) | (0.000) | 0.000$^{*}$ | 0.002$^{***}$ | 0.003$^{***}$ | 0.001 | 0.000 |
| Percent Gov. Employed (%) | 0.022$^{**}$ | -0.000 | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) |
| | (0.009) | (0.000) | -0.001$^{**}$ | -0.001 | 0.001 | 0.001 | 0.000 |
| Percent w/ Children (%) | 0.009$^{**}$ | 0.001$^{***}$ | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) |
| | (0.005) | (0.000) | -0.000 | 0.001$^{***}$ | 0.003$^{***}$ | 0.000 | 0.001$^{**}$ |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,655,952 | 3,655,952 | 3,655,952 | 3,655,952 | 3,655,952 | 3,655,952 | 3,655,952 |
| Adjusted $R^2$ | 0.688 | 0.703 | 0.879 | 0.425 | 0.208 | 0.688 | 0.549 |

**Table 8:** Natural Disaster Relief, Foreclosure, and Divorce

The outcome variable in Column (1), *Foreclosure,* equals one if the individual experiences a foreclosure and zero otherwise. The outcome variable in Column (2), *Divorce*, equals one hundred when the individual changes their marital status from married to single and zero otherwise. *Natural Disaster-Assistance* is an indicator variable that equals one if the credit bureau has indicated the individual has at least one credit account affected by a natural disaster, and zero otherwise. Variables delineated as *High* are indicator variables that equal one if the individual lives in a census tract in the top decile of that characteristic, and zero otherwise. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are reported in parentheses. All interaction terms are lagged *, **, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) |
|---|---|---|
| | (First stage)<br>Foreclosure | (Second stage)<br>Divorce |
| Natural Disaster Assistance | -0.002*** | |
| | (0.000) | |
| Foreclosure | | 1.061*** |
| | | (0.410) |
| High Collections (Med) | 0.637*** | -0.304 |
| | (0.090) | (0.298) |
| Credit Score Bins | -0.013*** | 0.011** |
| | (0.000) | (0.006) |
| Log(Estimated Income) | 1.079*** | 0.462 |
| | (0.308) | (0.771) |
| Log(Estimated Income)$^2$ | -0.086*** | -0.111 |
| | (0.032) | (0.074) |
| Age | -0.001 | 0.059*** |
| | (0.002) | (0.004) |
| Poverty Rate (%) | 0.000*** | 0.002*** |
| | (0.000) | (0.000) |
| Log(Population Density) | 0.000 | 0.015*** |
| | (0.000) | (0.000) |
| Minority Share (%) | 0.000** | 0.001*** |
| | (0.000) | (0.000) |
| Household Size | -0.002*** | -0.047*** |
| | (0.000) | (0.001) |
| Percent HS Diploma (%) | 0.000*** | -0.001*** |
| | (0.000) | (0.000) |
| Percent Govt. Employed (%) | 0.000 | -0.000*** |
| | (0.000) | (0.000) |
| Percent Hh w/ Children (%) | 0.000* | -0.001*** |
| | (0.000) | (0.000) |
| Year FE | Yes | Yes |
| Individual FE | Yes | Yes |
| Observations | 3,655,952 | 3,655,952 |
| F-statistic | 44.525 | - |

**Table 9:** Hazard Model

This table shows the non-exponentiated coefficient estimates of a Cox proportional hazard model on the incidence of divorce based on equation (3). For this analysis, the sample is constructed by limiting observations to individuals who were married at some point from 2011-2019. The individual enters the sample during the first year the person is married. The last year of record for the individual is the earlier of (i) the year of first divorce (during 2011-2019) and (ii) the last year of observation if no divorce occurs. We define failure as when a married individual experiences divorce (i.e., marital termination). *Foreclosure Flag* is an indicator variable that equals one when the individual has experienced a foreclosure event in the current period or past periods, and zero otherwise. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the individual level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>All | (2)<br>Female Only |
|---|---|---|
| Foreclosure Flag | 0.149*** | 0.143*** |
| | (0.012) | (0.020) |
| High Collections (Med) | 0.086*** | 0.084*** |
| | (0.006) | (0.009) |
| Credit score | -0.002*** | -0.002*** |
| | (0.000) | (0.000) |
| Homeowner | -0.470*** | -0.443*** |
| | (0.005) | (0.007) |
| Log(Estimated Income) | 0.765*** | 0.763*** |
| | (0.032) | (0.053) |
| Log(Estimated Income)$^2$ | -0.127*** | -0.135*** |
| | (0.004) | (0.006) |
| Age | -0.026*** | -0.027*** |
| | (0.000) | (0.000) |
| Female | -0.063*** | |
| | (0.003) | |
| Poverty Rate (%) | 0.020*** | 0.019*** |
| | (0.000) | (0.000) |
| Log(Population Density) | 0.228*** | 0.231*** |
| | (0.001) | (0.002) |
| Minority Share (%) | 0.007*** | 0.007*** |
| | (0.000) | (0.000) |
| Household Size | -0.565*** | -0.538*** |
| | (0.007) | (0.010) |
| Percent HS Diploma (%) | -0.004*** | -0.003*** |
| | (0.000) | (0.000) |
| Percent Govt. Employed (%) | -0.007*** | -0.006*** |
| | (0.000) | (0.001) |
| Percent w/ Children (%) | -0.006*** | -0.006*** |
| | (0.000) | (0.000) |
| Observations | 6,985,087 | 3,063,687 |

**Table 10:** Excluding Local Economic Shocks

This table shows the OLS regression results of the sample of borrowers in census tracts with no local employment shocks. A tract is defined to have experienced no local shocks if the absolute value of the difference between the tract-year-level ratios, Change in Tradable Employment Ratio, and Change in Non- tradable Employment Ratio is less than or equal to two times the standard deviation of the difference between the Change in Tradable Employment Ratio and Change in Non-tradable Employment Ratio across all tracts from 2009 to 2019. Change in Tradable Ratio is defined as the difference between tradable employment/total employment in year t and tradable employment/total employment in year t-1. Change in Non-tradable Ratio is defined as the difference between non-tradable employment/total employment in year t and non-tradable employment/total employment in year t-1. The outcome variable, *Divorce*, is equal to one hundred for individual who change their marital status from married to single, and zero otherwise. The following variables are lagged: *Repossession*, *High Collections (Non-Med)*, *Being Delinquent*, *Bankruptcy*, *High Collections (Med)*, *Credit score*, *Homeowner*, *Log(Estimated Income)*, and *Log(Estimated Income)*. In this analysis, we limit our observations to individuals who are married in the prior period. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Foreclosure | 0.511*** | | | | | 0.421*** |
| | (0.166) | | | | | (0.161) |
| Repossession | | 0.429 | | | | 0.276 |
| | | (0.309) | | | | (0.300) |
| High Collections (Non-Med) | | | 0.393*** | | | 0.383*** |
| | | | (0.069) | | | (0.067) |
| Being Delinquent | | | | 0.337*** | | 0.336*** |
| | | | | (0.033) | | (0.034) |
| Bankruptcy | | | | | 0.056 | -0.074 |
| | | | | | (0.131) | (0.130) |
| High Collections (Med) | 0.712*** | 0.711*** | 0.717*** | 0.713*** | 0.711*** | 0.751*** |
| | (0.082) | (0.082) | (0.083) | (0.082) | (0.082) | (0.082) |
| Credit score | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Homeowner | -1.411*** | -1.404*** | -1.402*** | -1.417*** | -1.405*** | -1.423*** |
| | (0.043) | (0.043) | (0.043) | (0.043) | (0.043) | (0.042) |
| Log(Estimated Income) | 7.466*** | 7.473*** | 7.466*** | 7.537*** | 7.471*** | 7.511*** |
| | (0.521) | (0.521) | (0.521) | (0.521) | (0.521) | (0.516) |
| Log(Estimated Income)$^2$ | -0.832*** | -0.833*** | -0.832*** | -0.839*** | -0.833*** | -0.836*** |
| | (0.056) | (0.056) | (0.056) | (0.056) | (0.056) | (0.055) |
| Age | -0.014** | -0.014** | -0.014** | -0.014** | -0.014** | -0.012* |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Poverty Rate (%) | 0.345*** | 0.345*** | 0.345*** | 0.345*** | 0.345*** | 0.344*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.010) |
| Log(Population Density) | 2.615*** | 2.615*** | 2.614*** | 2.614*** | 2.615*** | 2.623*** |
| | (0.090) | (0.090) | (0.090) | (0.090) | (0.090) | (0.088) |
| Minority Share (%) | 0.154*** | 0.154*** | 0.154*** | 0.154*** | 0.154*** | 0.156*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Household Size | -8.761*** | -8.761*** | -8.759*** | -8.758*** | -8.761*** | -8.833*** |
| | (0.383) | (0.383) | (0.383) | (0.383) | (0.383) | (0.387) |
| Percent HS Diploma (%) | -0.044*** | -0.044*** | -0.044*** | -0.044*** | -0.044*** | -0.047*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) |
| Percent Govt. Employed (%) | -0.110*** | -0.110*** | -0.110*** | -0.110*** | -0.110*** | -0.109*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Percent w/ Children (%) | -0.076*** | -0.076*** | -0.076*** | -0.076*** | -0.076*** | -0.075*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Individual, Year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,598,766 | 8,598,766 | 8,598,766 | 8,598,766 | 8,598,766 | 8,842,969 |
| Adjusted $R^2$ | 0.259 | 0.259 | 0.259 | 0.259 | 0.259 | 0.260 |

# Financial  Breakups: Till Debt Do Us Part

## Internet Appendix

## **Table IA.1:** Financial Distress Types and Divorce (Female Only)

This analysis is restricted to female individuals. The outcome variable, *Divorce*, is a variable that equals one hundred when the individual changes their marital status from married to single, and zero otherwise. *Foreclosure* is an indicator variable that equals one when an individual had a foreclosure in the last 12 months, and zero otherwise. *Repossession* is an indicator variable that equals one when an individual had an auto repossession in the last 12 months, and zero otherwise. *High Collections (Non-Med)* is an indicator variable that equals one when the individual is in the top tercile of the distribution of non-medical debt in collections, and zero otherwise. *Being Delinquent* is an indicator variable that equals one when an individual is delinquent on any credit product for 30 days or more in the last 12 months, and zero otherwise. *Bankruptcy* is an indicator variable that equals one when an individual had a bankruptcy filing in the last 12 months, and zero otherwise. The following variables are lagged: *Repossession*, *High Collections (Non-Med)*, *Being Delinquent*, *High Collections (Med)*, *Log(Credit Score)*, *Homeowner*, *Log(Estimated Income)*, and *Log(Estimated Income)*2. In this analysis we limit our observations to individuals who are married in the prior period. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Foreclosure | 0.361 | | | | | 0.334 |
| | (0.257) | | | | | (0.257) |
| Repossession | | -0.016 | | | | -0.080 |
| | | (0.495) | | | | (0.493) |
| High Collections (Non-Med) | | | 0.267*** | | | 0.283*** |
| | | | (0.103) | | | (0.103) |
| Being Delinquent | | | | 0.223*** | | 0.228*** |
| | | | | (0.054) | | (0.053) |
| Bankruptcy | | | | | -0.142 | -0.180 |
| | | | | | (0.188) | (0.189) |
| High Collections (Med) | 0.686*** | 0.686*** | 0.692*** | 0.700*** | 0.687*** | 0.709*** |
| | (0.114) | (0.114) | (0.114) | (0.114) | (0.114) | (0.114) |
| Log(Credit Score) | -1.605*** | -1.626*** | -1.531*** | -1.137*** | -1.640*** | -1.026*** |
| | (0.291) | (0.290) | (0.290) | (0.304) | (0.291) | (0.303) |
| Homeowner | -1.161*** | -1.156*** | -1.155*** | -1.159*** | -1.155*** | -1.159*** |
| | (0.052) | (0.052) | (0.052) | (0.052) | (0.052) | (0.052) |
| Log(Estimated Income) | 4.621*** | 4.627*** | 4.608*** | 4.580*** | 4.630*** | 4.558*** |
| | (0.689) | (0.689) | (0.688) | (0.689) | (0.689) | (0.688) |
| Log(Estimated Income)$^2$ | -0.534*** | -0.535*** | -0.533*** | -0.531*** | -0.535*** | -0.529*** |
| | (0.072) | (0.072) | (0.072) | (0.072) | (0.072) | (0.072) |
| Log(Age) | 4.828*** | 4.825*** | 4.817*** | 4.774*** | 4.824*** | 4.767*** |
| | (0.605) | (0.605) | (0.605) | (0.603) | (0.605) | (0.602) |
| Poverty Rate (%) | 0.310*** | 0.310*** | 0.310*** | 0.310*** | 0.310*** | 0.310*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Log(Population Density) | 2.521*** | 2.521*** | 2.521*** | 2.521*** | 2.521*** | 2.521*** |
| | (0.085) | (0.085) | (0.085) | (0.085) | (0.085) | (0.085) |
| Minority Share (%) | 0.153*** | 0.153*** | 0.153*** | 0.153*** | 0.153*** | 0.153*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Household Size | -8.347*** | -8.347*** | -8.346*** | -8.346*** | -8.348*** | -8.345*** |
| | (0.395) | (0.395) | (0.395) | (0.395) | (0.395) | (0.395) |
| Percent HS Diploma (%) | -0.038*** | -0.038*** | -0.038*** | -0.038*** | -0.038*** | -0.038*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Percent Govt. Employed (%) | -0.098*** | -0.098*** | -0.098*** | -0.098*** | -0.098*** | -0.098*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Percent w/ Children (%) | -0.059*** | -0.059*** | -0.059*** | -0.059*** | -0.059*** | -0.059*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,850,232 | 3,850,232 | 3,850,232 | 3,850,232 | 3,850,232 | 3,850,232 |
| Adjusted $R^2$ | 0.267 | 0.267 | 0.267 | 0.267 | 0.267 | 0.267 |

## **Table IA.2:** Logit Model

This table shows logistic regression results. The dependent variable is the log-odds of divorce. *Divorce* is a variable that equals one hundred when the individual changes their marital status from married to single, and zero otherwise. *Financial Distress Event* is an indicator variable that equals one when the individual has one of the following events in their credit history in a given year: bankruptcy, foreclosure, or lagged repossession, and zero otherwise. *Foreclosure* is an indicator variable that equals one when an individual had a foreclosure in the last 12 months, and zero otherwise. *Repossession* is an indicator variable that equals one when an individual had an auto repossession in the last 12 months, and zero otherwise. *High Collections (Non-Med)* is an indicator variable that equals one when the individual is in the top tercile of the distribution of non-medical debt in collections, and zero otherwise. *Being Delinquent* is an indicator variable that equals one when an individual is delinquent on any credit product for 30 days or more in the last 12 months, and zero otherwise. *Bankruptcy* is an indicator variable that equals one when an individual had a bankruptcy filing in the last 12 months, and zero otherwise. The following variables are lagged: *Repossession*, *High Collections (Non-Med)*, *Being Delinquent*, *High Collections (Med)*, *Log(Credit Score)*, *Homeowner*, *Log(Estimated Income)*, and *Log(Estimated Income)*$^2$. In this analysis we limit our observations to individuals who are married in the prior period. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Financial Distress Event | 0.075*** | | | | | | |
| | (0.013) | | | | | | |
| Foreclosure | | 0.202*** | | | | | 0.212*** |
| | | (0.022) | | | | | (0.022) |
| Repossession | | | 0.105*** | | | | 0.093*** |
| | | | (0.025) | | | | (0.025) |
| High Collections (Non-Med) | | | | 0.187*** | | | 0.187*** |
| | | | | (0.007) | | | (0.007) |
| Being Delinquent | | | | | -0.020*** | | -0.016*** |
| | | | | | (0.005) | | (0.005) |
| Bankruptcy | | | | | | -0.054*** | -0.067*** |
| | | | | | | (0.020) | (0.020) |
| High Collections (Med) | 0.116*** | 0.117*** | 0.116*** | 0.104*** | 0.113*** | 0.116*** | 0.102*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Log(Credit Score) | -1.347*** | -1.348*** | -1.354*** | -1.193*** | -1.395*** | -1.361*** | -1.212*** |
| | (0.028) | (0.028) | (0.028) | (0.027) | (0.029) | (0.028) | (0.028) |
| Homeowner | -0.552*** | -0.554*** | -0.551*** | -0.546*** | -0.549*** | -0.551*** | -0.547*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Log(Estimated Income) | 1.151*** | 1.149*** | 1.158*** | 1.105*** | 1.184*** | 1.162*** | 1.116*** |
| | (0.090) | (0.090) | (0.090) | (0.090) | (0.090) | (0.090) | (0.090) |
| Log(Estimated Income)$^2$ | -0.179*** | -0.179*** | -0.180*** | -0.175*** | -0.183*** | -0.180*** | -0.176*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Log(Age) | -1.321*** | -1.321*** | -1.321*** | -1.327*** | -1.322*** | -1.321*** | -1.327*** |
| | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) |
| Female | -0.053*** | -0.053*** | -0.053*** | -0.054*** | -0.052*** | -0.053*** | -0.054*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Poverty Rate (%) | 0.026*** | 0.026*** | 0.026*** | 0.026*** | 0.026*** | 0.026*** | 0.026*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Log(Population Density) | 0.287*** | 0.287*** | 0.287*** | 0.286*** | 0.287*** | 0.287*** | 0.286*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Minority Share (%) | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.010*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Household Size | -0.812*** | -0.812*** | -0.811*** | -0.811*** | -0.811*** | -0.811*** | -0.811*** |
| | (0.042) | (0.042) | (0.042) | (0.042) | (0.042) | (0.042) | (0.042) |
| Percent HS Diploma (%) | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Percent Govt. Employed (%) | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.008*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Percent w/ Children (%) | -0.005*** | -0.005*** | -0.005*** | -0.005*** | -0.005*** | -0.005*** | -0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 9,189,581 | 9,189,581 | 9,189,581 | 9,189,581 | 9,189,581 | 9,189,581 | 9,189,581 |

**Table IA.3:** The Direct Effect of Natural Disaster Assistance on Divorce

The outcome variable, *Divorce*, is a variable that equals one hundred when the individual changes their marital status from married to single and zero otherwise. *Natural Disaster-Assistance* is an indicator variable that equals one if the credit bureau has indicated the individual has at least one account affected by a natural disaster, and zero otherwise. Column (1) uses the full sample, and Column (2) excludes from the sample individuals that experience a foreclosure. Variables delineated as *High* are indicator variables that equals one if the individual lives in a census tract in the top decile of that characteristic, and zero otherwise. We define variables in Table Variable Definitions of the Appendix. Robust standard errors are adjusted for clustering at the county level and are reported in parentheses. All interaction terms are lagged *, **, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Divorce (%) | |
|---|---|---|
| | (1) | (2) |
| | Full Sample | Excluding Foreclosed |
| Natural Disaster Assistance | -0.086 | -0.084 |
| | (0.090) | (0.089) |
| Credit Score Bins | -0.003*** | -0.003*** |
| | (0.000) | (0.000) |
| Log(Estimated Income) | 0.984 | 0.981 |
| | (0.659) | (0.656) |
| Log(Estimated Income)$^2$ | -0.132* | -0.131* |
| | (0.067) | (0.067) |
| Age | -0.001 | -0.002 |
| | (0.008) | (0.008) |
| Poverty Rate (%) | 0.196*** | 0.193*** |
| | (0.008) | (0.008) |
| Log(Population Density) | 1.501*** | 1.486*** |
| | (0.073) | (0.073) |
| Minority Share (%) | 0.114*** | 0.114*** |
| | (0.006) | (0.006) |
| Household Size | -5.215*** | -5.155*** |
| | (0.273) | (0.273) |
| Percent HS Diploma (%) | -0.057*** | -0.058*** |
| | (0.010) | (0.010) |
| Percent Govt. Employed (%) | -0.051*** | -0.050*** |
| | (0.010) | (0.010) |
| Percent Hh w/ Children (%) | -0.063*** | -0.063*** |
| | (0.007) | (0.007) |
| Constant | 10.169*** | 10.058*** |
| | (1.992) | (2.011) |
| Individual FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 3,655,952 | 3,630,866 |
| Adjusted $R^2$ | 0.193 | 0.193 |