Credit When You Need It*

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Abstract

We estimate the causal effect of credit provision on the household balance sheet. To do so, we link application data from the U.S. Federal Disaster Loan program, which provides loans to households that have uninsured damages from a federally-declared natural disaster, to a panel of credit records before and after the shock. We exploit discontinuous variation in loan approval rules, which led those with debt-to-income ratios below 40% to be differentially likely to be approved. Using an instrumented difference-in-differences research design, we find that credit provision at the time of a shock can significantly reduce the worst outcomes, decreasing the likelihood of loan delinquency by 20% and the likelihood of bankruptcy by 17%. Credit provision in a time of crisis has real consumption effects in the form of additional car purchases even 3 years after loan receipt. Our findings suggest that well-timed liquidity provided to households in acute need can have substantial and persistent positive effects.

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1 Introduction

Credit allows households to smooth shocks over time that might otherwise lead to financial distress. In particular, credit provides liquidity, and many households are illiquid. Only 40% of U.S. households report that they have enough liquid savings to cover 3 months of expenses (Bhutta and Dettling, 2018). Some shocks are much larger: A major natural disaster, health expense, or liability suit, for instance, can create a sudden and substantial uninsured financial obligation. In the absence of credit, this large need represents a financing challenge that most families would be unable to solve. Unaddressed needs can fester, creating a liquidity crisis. Growing unpaid bills can lead to mounting fees and penalties, account delinquencies, falling credit scores, and even personal bankruptcy. By providing immediate liquidity that can be repaid gradually, credit may stave off a financial cascade.

While borrowing to smooth large financial obligations is theoretically straightforward (e.g., Friedman, 1957), empirical research highlights adjustment frictions and other barriers that may preclude households' ability to do so. Existing consumption commitments, such as mortgage and auto loan payments and other household expenses, can leave little room to service additional debt (Chetty and Szeidl, 2007). Recent studies find that adjusting such commitments is even more difficult than previously appreciated (Boar et al., 2022; Ganong and Noel, 2020). Thus, attempting to borrow one's way out of a crisis might delay but ultimately exacerbate financial distress. Can households reduce the consequences of severe events through borrowing?

Empirically assessing the impact of credit on households' financial health is difficult for at least three reasons. First, credit provision is inherently endogenous because lenders underwrite on financial health (Agarwal et al., 2018). Second, households may differ in the likelihood of experiencing a shock on both observable and unobservable dimensions. Finally, consumers who turn to credit in an emergency may differ on many characteristics (e.g., attitudes toward debt) from those who do not. Assessing the impact of credit, therefore, requires a setting with comparable consumers facing exogenous liquidity needs and credit provision that is plausibly randomly assigned.

In this paper, we examine the effects of credit supplied by the U.S. Federal Disaster Loan program, which provides loans to households that have uninsured damages from a federally-declared natural disaster. These loan applications are carefully underwritten by the program and include information on credit scores, other debts, and household income. Our data include 290,000 applications for disaster loans, spanning 324 presidentially-declared disasters from 2005 to 2012, merged to credit record data from Experian, one of the nation's three large credit bureaus.

Through this merge, we can observe a balanced panel of applicants' credit records from 18 months before to 3.5 years after the disaster.

This setting is ideal for examining the use of credit to manage large shocks. The average applying household had over $75,000 in damages, an amount representing more than 125% of its annual income. Households commonly incur large, sudden, uninsured losses when a major hurricane occurs due to inefficiencies in U.S. flood insurance markets (Michel-Kerjan, 2010). Many households would presumably have difficulty funding the cost of recovery without credit. The average loan received is for $50,000, with a term of 21 years, at an interest rate of 2.5%, yielding average monthly payments of $250. Through this loan, households can spread the immediate cost of repairs over the next two decades.

To identify the causal effect of credit provision, we instrument for loan approval using a discontinuity in the likelihood of being approved around a debt-to-income (DTI) ratio of 0.4, which is codified into the loan handbook (Office of Disaster Assistance, 2018). We find that the likelihood of approval jumps by 12 percentage points (from 54% to 66%) around the DTI threshold. This estimation yields a strong first stage and, combined with no evidence of DTI manipulation or other applicant attributes varying around the threshold, suggests that we can make causal inferences in this quasi-experimental setting.

We use a difference-in-differences design to examine how approval for a disaster loan affects private credit outcomes such as debt balances, delinquencies, and bankruptcy in the years following a natural disaster. Each disaster in our analysis includes unique treatment and control groups; we stack the datasets to estimate and report an average response across all disasters.

We pursue three questions regarding emergency credit and households' finances. First, does emergency credit reduce financial distress in the years after the event? Second, does emergency credit improve recovery outcomes including new outlays for durable goods? Third, what mechanisms explain these results?

First, we find that receiving credit after a disaster persistently reduces financial distress. Our estimates indicate that applicants who receive the loan due to the discontinuity in approval are 17% less likely to file for bankruptcy, even 3.5 years after the disaster. With rich credit report data, we can trace out the path of a "debt spiral" to show that new, affordable credit reduces delinquencies that precede bankruptcy. We find that the loan reduces the likelihood of delinquencies by 20% within a year of the disaster. These delinquencies predate the largest effects on bankruptcy, which occur around 2 years after the disaster, illustrating that as consumers fall behind on payments, their debts can become insurmountable.

We also find evidence of a "pecking order" of defaults regarding how households prioritize repayment of different types of debts (Andersson et al., 2013). We find a reduction in delinquencies across a variety of household debt categories: Credit cards, auto loans, and mortgages, are significantly less likely to be delinquent after loan receipt. Credit cards are the first type of account that consumers fall behind on after a disaster, followed by auto loans and then mortgages. This prioritization of credit cards appears consistent with households choosing among which types of debt to repay in order to minimize the immediate penalties and interest charges of skipping a payment. Moreover, it illustrates the types of mounting costs that can accrue for households who do not receive a recovery loan.

This long-lasting effect on reducing delinquencies and bankruptcy filing is robust to a range of specification choices and the inclusion of a variety of observable covariates and fixed effects, consistent with the quasi-experimental design. Applicants had no differential levels or trends in delinquency prior to the disaster. We are further able to rule out that delinquency is simply being shifted from private to public markets, as total charge-offs, which include debts from the program itself, fall upon (instrumented) loan receipt. These findings suggest that well-targeted credit provision at the time of a shock can mitigate the worst outcomes.

Our second main finding is that credit provision at the time of a disaster affects household consumption and ultimately the real economy. We estimate that applicants who receive the loan due to the approval discontinuity are 5 percentage points more likely to take out a new auto loan, which is usually associated with purchasing a car. Relative to the baseline rate of roughly 8 percent per year, this response is large, and the effect on new auto purchases persists for 3.5 years. Auto loan behavior is parallel and similar in magnitude prior to the disaster, but those who receive the loan differentially increase their auto borrowing thereafter. These leveraged auto purchases suggest that, rather than "crowding out," these government loans in fact "crowd in" borrowing from private credit markets.

Third, we explore the potential mechanisms generating these meaningful effects of credit on financial distress and household consumption. Disaster recovery loans bundle two features that might explain the results. The first is that they may allow households to solve a substantial financing problem. The second potential benefit is that these subsidized, low-interest loans represent a wealth transfer to consumers.

To disentangle these mechanisms, we leverage additional exogenous variation in the program's interest rates. Approved applicants with credit scores above 700 are typically offered an interest rate of approximately the private market's concurrent 30-year, fixed-rate mortgage interest rate. Approved applicants with credit scores below 700 are offered an interest rate of approximately half that rate. Examining outcomes around this price discontinuity, we find no evidence that the benefits of recovery loans depend on receiving the lower interest rate. This result suggests that the loan's benefits arise through the provision of emergency liquidity rather than the wealth transfer, aligning with recent findings highlighting the role of liquidity in understanding household financial distress (Boar et al., 2022; Ganong and Noel, 2020).

Finally, to examine links between liquidity needs and financial distress, we obtained survey data on how households fund disaster repairs (You and Kousky, 2022) to complement our credit report data. Many households in the survey report combining several sources of funding. The most common funding source – used by over half of all respondents – is savings, followed by assistance from family and friends. Households also report delaying medical care, reducing consumption, and falling behind on existing bills like credit cards and rent. The survey data offer a richer view of households who are stretching their means to address liquidity needs, including through coping strategies that may have persistent negative consequences.

Our work provides some of the first causal evidence that a well-timed infusion of low-cost credit can reduce the likelihood of a household entering into a debt spiral that ultimately ends in bankruptcy. Other recent research studying household financial distress include Gross et al. (2021), which examines the effects of changing incentives around personal bankruptcy reform, while Keys et al. (2020) uses a movers design to explore the drivers of household financial distress and bankruptcy.

Our findings advance the literature on the importance of credit markets for consumption smoothing and the role of liquidity in household financial decision-making. Agarwal et al. (2018) shows that during the Great Recession, lenders directed credit toward lower risk households instead of those with the greatest credit demand. Hurst and Stafford (2004) and Amromin et al. (2020) study the role of liquidity from home equity in smoothing household shocks, while Kaplan et al. (2014) find that many households, even relatively well-off ones, may have little liquidity to smooth income disruptions.

Our finding that public credit in the form of a Federal Disaster Loan increases the likelihood of a new auto loan is new evidence in the long-standing debate of whether public programs crowd out private investment (Aschauer, 1989). By allowing consumers to address their emergency expenses, these disaster loans appear to help households recover and further generate private sector lending opportunities in the years following the event. We are thus able to provide new causal evidence that public policy interventions to alleviate liquidity constraints can expand, rather than hinder, private credit markets.

Finally, our analysis extends the growing body of research examining the economic consequences of climate risk (e.g., Bernstein et al., 2019; Addoum et al., 2020; Keys and Mulder, 2020; Krueger et al., 2020). Almost 36 million U.S. homes – 43% of all U.S. homes with a $6.6 trillion combined market value – are exposed to natural disaster risk (RealtyTrac, 2015). As the frequency and severity of disasters are increasing (Hsiang and Kopp, 2018), resulting in 20 billion-dollar disasters in 2021 alone, furthering our understanding of how households are affected by climate is a growing priority. Gallagher and Hartley (2017) investigates the consequences of Hurricane Katrina on household balance sheets. Gallagher et al. (2023) looks at the financial impact of living in the path of a tornado, and the associated disaster aid programs that can mitigate harmful effects. We assess a large and important federal lending program, which supports households experiencing natural disasters (Collier and Ellis, 2021; Collier et al., 2021; Billings et al., 2021; Begley et al., 2020). By matching detailed disaster loan applications with consumer credit reports for the first time, we provide novel estimates of the causal effects of receiving an emergency loan in the aftermath of a disaster on household financial well-being.

2 Data and Setting

This section describes the Federal Disaster Loan (FDL) program and our data, using material from FEMA (2019) and the program's Office of Disaster Assistance (2018).

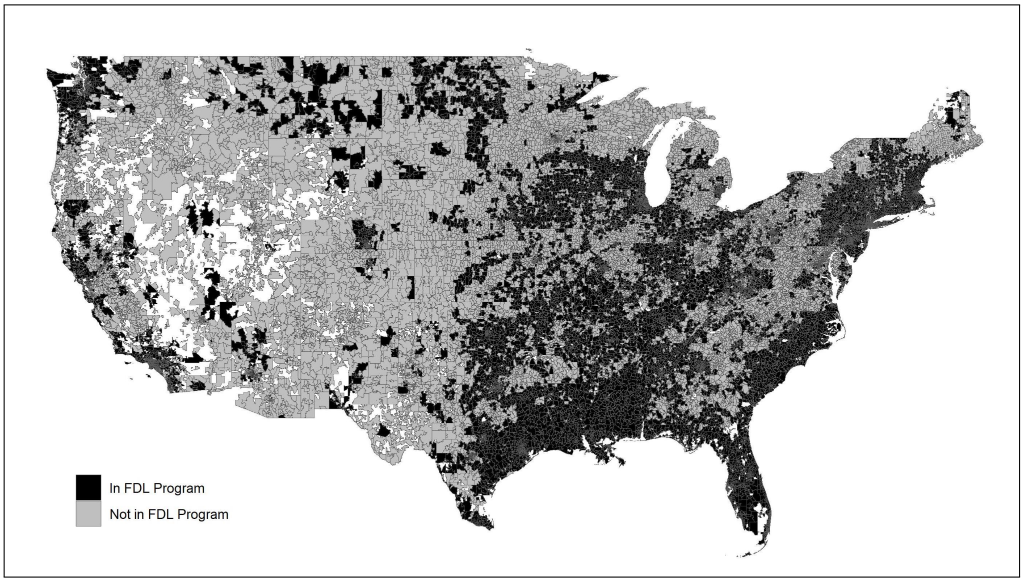
2.1 Federal Disaster Loan Program Overview

Since its inception in 1953, the FDL program has made roughly $60 billion in recovery loans as of 2019. Administered by the Small Business Administration (SBA), the program is authorized to lend to households for the repair of uninsured damages to their primary residence, its contents (e.g., appliances, furniture), and their automobiles. Though it predominantly lends to households, the program also lends to businesses and non-profits. In 2017, households comprised 80% of applicants and 70% of the total loan volume. We limit our analysis to household lending.

Effectively all (98%) household FDL applications are associated with a presidential disaster declaration. For these declarations, FEMA coordinates the local response, establishing temporary offices in affected neighborhoods. Households harmed by the disaster are encouraged to register with these FEMA offices. Households with incomes below a certain threshold (typically 125% of the federal poverty line) are referred to a FEMA grant program, which pays to repair or replace their lost property. FEMA refers households above the income threshold to the FDL program to apply for a loan. These households are then automatically contacted (via email, robocalls, and letters) by the FDL program.

A household's eligibility depends on the issuance of a disaster declaration for its county, incurring a loss from the disaster, and some portion of the loss being uninsured. Figure 1 shows the geographic distribution of the program, and illustrates its broad use across the contiguous U.S. with an emphasis on the Gulf and South Atlantic coasts. The black areas in the figure denote ZIP codes that have at least one borrower in the program between 2005 and 2012.

Figure 1: ZIP Codes with FDL Borrowers



Note: Figure shows which ZIP codes had at least one borrower in our sample.

2.2 Data and Summary Statistics

Our data include all household FDL applications from 1 January 2005 to 31 December 2012 in the 50 U.S. states and the District of Columbia. During that time, the program received over 460,685 completed applications and lent to 168,929 households. The program collects information on an applicant's income from the IRS, outstanding debts from credit reports, and property damages from an onsite loss inspection. Table 1 describes the income, credit scores, and existing debt-service-to-income (DTI) ratios of applicants and borrowers. The average credit scores of borrowers is 691, below that of GSE mortgage borrowers, but around the national average. The average borrower has a DTI of 39%, which is higher than GSE mortgage borrowers during this time.

Table 1: Summary Statistics of Federal Disaster Loan Borrowers

			Percentiles		
	Mean	SD	p10	p50	p90
All Applicants					
Income	69922	49465	30432	55012	122000
Credit Score	663	101	527	665	797
DTI	0.36	0.36	0.06	0.31	0.63
Loss Amount	81462	102804	9729	44791	200895
Indicator for Any Delinquent Loan	0.24	0.43	0.00	0.00	1.00
Amount Past Due on Delinquent Loans	1016	9919	0	0	558
Indicator for Bankruptcy	0.13	0.33	0.00	0.00	1.00
Number of New Auto Loans	0.09	0.30	0.00	0.00	0.00
Borrowers					
Income	73599	47410	32218	60443	127033
Credit Score	692	77	587	690	795
DTI	0.30	0.24	0.04	0.29	0.50
Loss Amount	87660	98582	11165	48259	219415
Indicator for Any Delinquent Loan	0.12	0.33	0.00	0.00	1.00
Amount Past Due on Delinquent Loans	196	3122	0	0	0
Indicator for Bankruptcy	0.11	0.31	0.00	0.00	1.00
Number of New Auto Loans	0.10	0.31	0.00	0.00	0.00
Interest Rate	2.72	0.74	1.69	2.69	2.94
Loan Duration (Months)	236	127	60	276	360
Monthly Payment	228	229	57	150	524
Loan Amount	42451	55704	8200	14000	119900

Note: Table includes data on 460,685 applicants and 168,929 borrowers for whom data on all variables listed are available. "Income" is annual adjusted gross income and is winsorized at the 99% level. "Credit Score" is the FICO score of the primary applicant. "DTI" divides a household's existing total monthly debt service payments (e.g., its mortgage) by its monthly income and is winsorized at the 99% level. "Loss Amount" is the program's onsite assessment of property losses. "Indicator for Any Delinquent Loan" is 1 if the individual has any loans reported 30 or more days delinquent on their credit file. "Amount Past Due" is the dollar amount past due on all loans 30 or more days delinquent. "Indicator for Bankruptcy" is 1 if there is a bankruptcy on the credit report. "Number of New Auto Loans" is the number of new auto tradelines in the last 6 months.
"Income", "Credit Score", "Loss Amount", and "DTI" are observed on the loan application. Credit variables for delinquency, bankruptcy, and new auto loans are measured using the Experian data in the period immediately prior to disaster declaration. "Loan Duration", "Monthly Payment" and "Loan Amount" are characteristics of the SBA disaster loan and thus only observed for households that borrow from the program.

2.3 Lending Decisions

The program is "a good faith lender and will only make a disaster loan if there is reasonable expectation that the loan can be repaid" (SBA, 2020). Lending decisions largely depend on the interaction of the applicant's credit score and *existing* debt-service-to-income (DTI) ratio (that excludes the new disaster loan). While the rules vary over time, the program generally approves applicants with a credit score of at least 620 and an existing DTI below 40. Approximately 50% of all applicants are approved.

The program can lend up to $200,000 for damages to the residence and up to a combined total of $40,000 in damages to their contents and automobiles. The average loan amount is $40,905 (median of $14,000) with a 2.72% interest rate, 20 year maturity, and $221 monthly payment (Table 1). While the program does not make lending decisions based on borrower collateral, the program requires borrowers to secure their loans with available collateralizable assets if the loan is above a certain amount (e.g., $25,000 as of 2018).[1]

The program allows for loans to be adjusted in cases of hardship by suspending payments and/or extending the loan's maturity, though interest on the loan continues to accrue during a deferment (Federal Register, 1997). For example, all disaster loans were granted an automatic deferment during COVID-19 (SBA, 2021). The program takes the following actions if the borrower defaults. First, the program transfers the delinquent debt to the Treasury Offset Program, which garnishes a portion of funds (e.g., tax refunds and social security payments) typically paid to an individual to pay down the loan balance (Treasury Offset Program, 2021). Second, the program reports the default to the credit bureaus who register it as charged-off Federal debt. Third, if the loan is collateralized, the program "may liquidate collateral securing a loan" (Federal Register, 2014).

2.4 Consumer Credit Reports

To conduct our analysis, we merge the application-level data from the Federal Disaster Loan program to credit report data provided by Experian, a national credit bureau and global information services company. Our merge was conducted using loan application information such as name, address at time of disaster, and social security number, and thus yielded a near-perfect match rate. Individual records are linked over time through a unique, anonymous consumer identification number assigned by Experian. To form our analysis sample, we take the applicants' records in June and December of each year from 2003 to 2015, seeking a balanced panel that runs 18 months prior to the disaster to 4 years after.

The Experian data includes information by broad loan category (e.g., mortgages, autos, credit cards) on the number of loans outstanding in the last six months, the total number of loans, total loan balances, total loan amounts, total credit limits, and delinquency status. Delinquency indica-

[1]Collier, Ellis, and Keys (2021) examine how the program's discontinuous collateral requirements affect consumers' borrowing and repayment decisions.

tors separately report the number of loans that have payments past due by more than 30, 60, 90, or 180 days or that have been sent to collections agencies. We also observe the total dollar amount of balances that are past due. Finally, we observe the total number of bankruptcies ever associated with an individual.

3 Estimation Strategy

3.1 Empirical Specification

Our goal is to estimate the causal effect of access to low-interest credit on financial health during a time of need. To motivate our empirical approach we consider the following event study specification which specifies the evolution of household financial outcomes,

$$y_{it} = \sum_{h=-a}^{b} \beta_h (1[t = h] \times APRV_i) + \Theta X_{itzd} + \epsilon_{it}$$

where y_{it} is an outcome for individual i at time t that was living in zip code z when disaster d struck. The β_h are the event time coefficients of interest. Time t is in event time. We observe applicants' credit records every six months (the reports are pulled on June 30 and December 31), starting approximately 1.5 years before the disaster (a) to 3 years after the disaster (b). $APRV_i$ is a variable for whether the loan was approved, a and b are the number of leads and lags included, and $1[\cdot]$ is the indicator function. The X_{itzd} are a set of controls and ϵ_{it} is an error term.

The problem with simply estimating this event study specification with Ordinary Least Squares (OLS) is that it is likely that, even after controlling for all of the information included in the loan application (which we can observe), loan approval is still correlated with soft information that may be observable to the loan officer but not to the econometrician.

To overcome this endogeneity problem, we exploit a discontinuity in the probability of having an SBA disaster loan application accepted. The probability of loan acceptance is higher for applicants whose DTI ratio is just below 40% compared to applicants whose DTI ratio is just above 40%. This discontinuity was codified into the SBA's lending handbook from 2005 through 2011. Our design can be thought of as a stacked difference-in-differences design, where randomization into the treatment or control group occurs based on whether a household's DTI ratio is just above or below 40% when a disaster hits.[2] Focusing on disaster loan applicants ensures that these are households that have suffered a verified and uninsured loss from the disaster.

To examine the consequences of loan receipt over time, we estimate our stacked difference-in-differences regression discontinuity specification using two-stage least squares as

$$y_{it} = \sum_{h=-a}^{b} \beta_h (1[t=h] \times APRV_i) + \gamma_0 DTI_i + \gamma_1 (DTI_i \times BELOW_i) + \psi_{zd} + \tau_{td} + \epsilon_{it} \tag{1}$$

where DTI_i is the DTI ratio on the application, and $BELOW_i$ is an indicator for whether $DTI_i <$ 40%. The ψ_{zd} and τ_{td} represent zip code by disaster and calendar time by disaster fixed effects, respectively, and ϵ_{it} is an error term.[3] For each value of relative event time h in the summation above, the first stage equation is

$$\begin{aligned}(1[t = \widehat{h] \times A}PRV_i) &= \alpha_h (1[t=h] \times BELOW_i) \\ &\quad + \delta_0 DTI_i + \delta_1 (DTI_i \times BELOW_i) + \phi_{zd} + \kappa_{td} + \mu_{it}\end{aligned} \tag{2}$$

resulting in h first stage equations, (h endogenous variables, and h instruments) yielding a just-identified system of equations.

3.2 Sample Restrictions

We restrict our sample in two ways. First, we limit our sample to applicants who have a DTI near the 0.4 threshold, specifically, between 0.3 and 0.5.[4] Second, we keep only applicants associated with the years (2005–2011) in which the DTI threshold was important in guiding approval decisions. During this period, the underwriting process imposed a discontinuous approval rule, described in more detail below.

Figure 2 shows applicants' characteristics (e.g., credit score, age, amount requested, delinquencies, etc.) across levels of DTI in the analysis sample. Many of these characteristics appear unrelated to DTI such as the applicants' age and history of bankruptcy. Other vary with DTI. For example, applicants with lower DTIs request larger disaster loans, which may result from better off households having both lower DTIs and more valuable property that was damaged. Im-

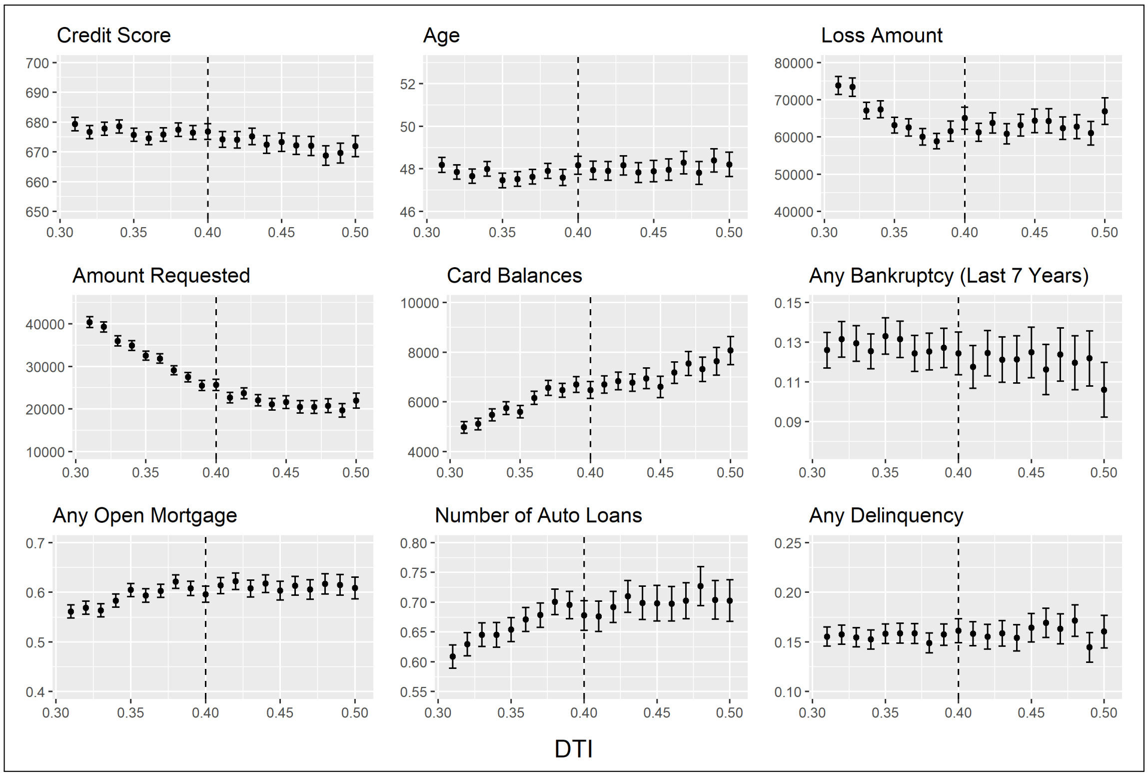
[2]A somewhat similar empirical strategy is employed in Cellini et al. (2010).

[3]Fitting zip code and time fixed effects separately for each disaster creates clean controls for each event and is sometimes described as a "stacked" regression (Baker et al., 2022).

[4]Section 6 presents evidence showing that our results are robust to modifying the DTI bandwidth.

portantly, none of the characteristics appear to change discontinuously at the DTI threshold. We additionally provide detailed summary statistics on this analysis sample in Appendix A.

Figure 2: Applicant Characteristics by DTI

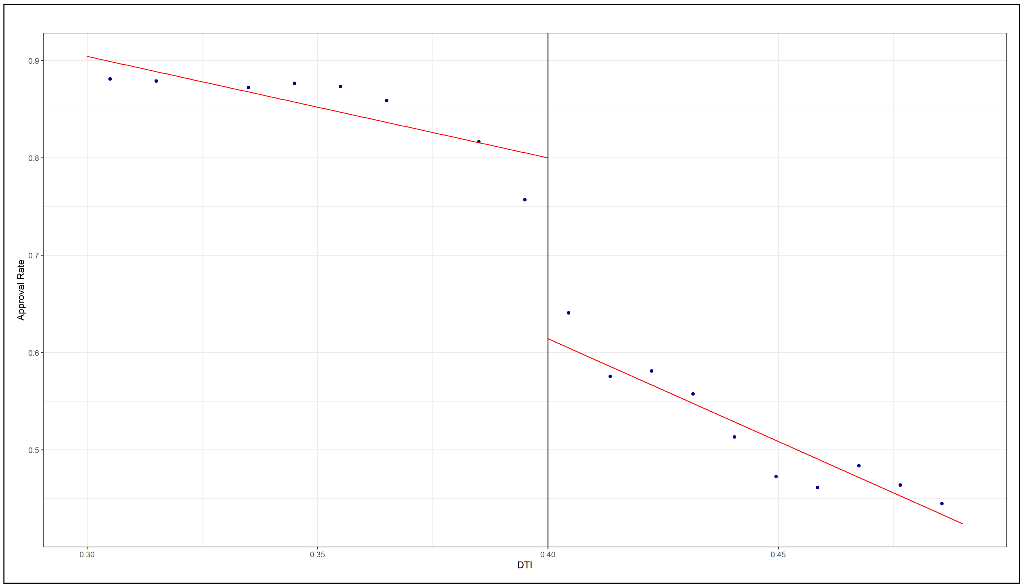


Note: Figure includes data on 59,336 applicants with debt-to-income ratios between 0.3 and 0.5. Each panel shows the average value of various applicant characteristics by bins of debt-to-income at loan application. All outcomes are measured in the period before disaster declaration. See Table 1 note for details on variable definitions.

3.3 First Stage

Figure 3 shows applicants' approval likelihoood by their debt-to-income ratio. The figure shows a clear discontinuity of nearly 20 percentage points crossing from below to above the DTI threshold. The two regimes are quite clear: Those applicants a few percentage points below 40% have an 80% chance of approval, while those a few percentage points above 40% have a 50% chance of approval that steadily declines thereafter. The figure shows that the underwriting process used this threshold to discontinuously and differentially evaluate applicants.

Figure 3: Change in Approval Likelihood at the Debt-to-Income Threshold, 2005–2011



Note: The figure shows the discontinuous change in the likelihood of loan approval for households below the DTI threshold of 40 relative to households above the threshold. Each point represents one percentage point of the DTI distribution.

4 Results

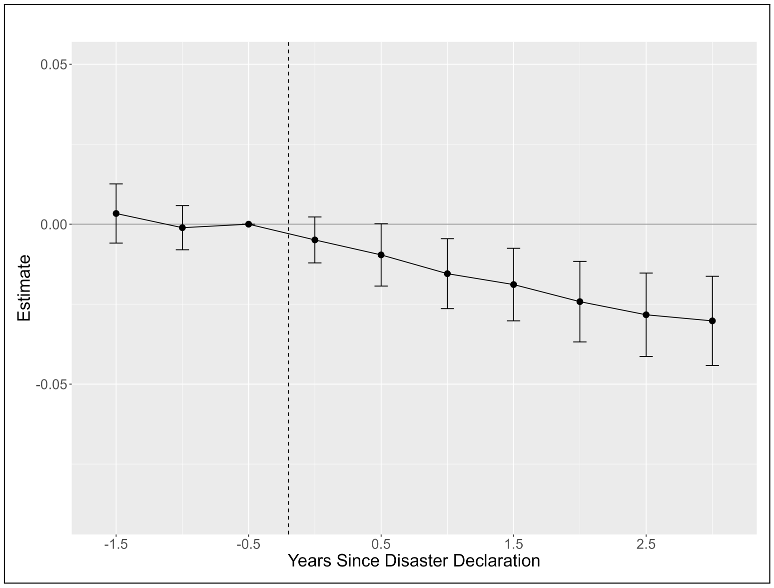
4.1 Household Financial Outcomes

We begin by examining whether the provision of an emergency liquidity loan affects the likelihood that a household declares bankruptcy. *A priori*, the direction of the effect is unclear. By increasing household leverage and committing more of the household's cash flows to servicing debt, emergency borrowing unambiguously increases standard metrics of the household's credit risk. Yet, emergency liquidity may allow a household to meet its immediate consumption needs – to repair or replace its home and other key durable goods. The benefits of doing so may outweigh the additional risks normally associated with increasing household debt.

Figure 4 shows the effect of loan approval on the propensity to have a bankruptcy on the credit report. The periods in the figure are 6-month intervals, starting 1.5 years prior and ending 3 years after the disaster. Period $t = -1$ represents the last observation before the disaster and serves as the reference period in the regressions. For example, Hurricane Irene made landfall in August 2011 so $t = -1$ represents the 30 June 2011 credit reports of households applying because of that event, while $t = 0$ represents the December 2011 credit report immediately after the event.

Figure 4 shows that loan approval leads to lower bankruptcy rates, and that these effects increase with time. The magnitude peaks two and a half years after the disaster at which point the effect of the loan reduces the probability of having a bankruptcy by 2.5pp. This translates to a 21% reduction in bankruptcy relative to the pre-disaster rate of 12.5pp.

Figure 4: Effect of Loan Approval on Likelihood of Bankruptcy



Note: The figure shows the local average treatment effect (LATE) of receiving a disaster loan on the likelihood of having a bankruptcy on the credit report using the DTI threshold as an instrument for approval.

How does loan approval lead to such a large reduction in severe financial distress that results in bankruptcy? Figure 5 presents the effect of loan approval on the likelihood of having any delinquent or derogatory debt, while Figure 6 shows the effect of loan approval on the total dollar amount of delinquent or derogatory debt. These measures reflect loan payments that are 30 or more days late. Figure 5 shows that loan approval has a large and persistent effect on the likelihood of delinquency beginning one year (2 periods) after the disaster. For example, 1.5 years after the disaster, approval reduces the likelihood of delinquency by 7 pp. Figure 6 similarly finds that, on average, loan approval reduces the amount delinquent on private balances by roughly $400 beginning 1.5 years after the disaster. Prior to the disaster, the mean derogatory or delinquent balance was $300 (Table A1).

By combining the results from Figures 5 and 6 we can consider the intensive margin effect of the increase in dollar amount of delinquency among consumers with delinquencies. Figure 5 provides the extensive margin effect of approval on the likelihood of having a delinquency $P(delinquent)$, and Figure 6 provides the unconditional effect of approval on the amount delinquent $E(amount)$. Thus, we can estimate $E(amount|delinquent)$ by taking the ratio of the two effects. Three periods after the disaster, we estimate that the average reduction in the amount delinquent for delinquent consumers is \$5,700.[5] Taken together, Figures 5 and 6 suggest meaningful extensive and intensive margin effects of loan approval on delinquency.

4.2 Heterogeneity by Loan Type

Figure 7 examines heterogeneity in the delinquency response across different types of loans. The figure shows the effect of loan receipt on the change in delinquency from six months before to 2.5 years after disaster declaration. Delinquency is measured using an indicator for ever having a delinquency of that loan type in the last 24 months. The figure shows that, among applicants with at least one mortgage, auto, and credit card loan prior to disaster declaration, loan receipt reduces the likelihood of having at least one credit card delinquency by 17 percentage points; the likelihood of mortgage delinquency falls by 11 percentage points, the likelihood of auto loan delinquency falls by 6 percentage points.

In Figure 7, we examine the how delinquencies of different loan types evolve over time using the conditional means of households above and below the DTI threshold. Households with with a DTI below 40 percent, shown in solid lines, were more likely to receive a loan, whereas those with a DTI above 40 percent, shown in dotted lines, were more likely to be denied (see the discussion of the first stage above). Here we examine the subsample with a DTI between 30 and 50 percent and who have an open mortgage, auto loan, and credit card in the period prior to the disaster.

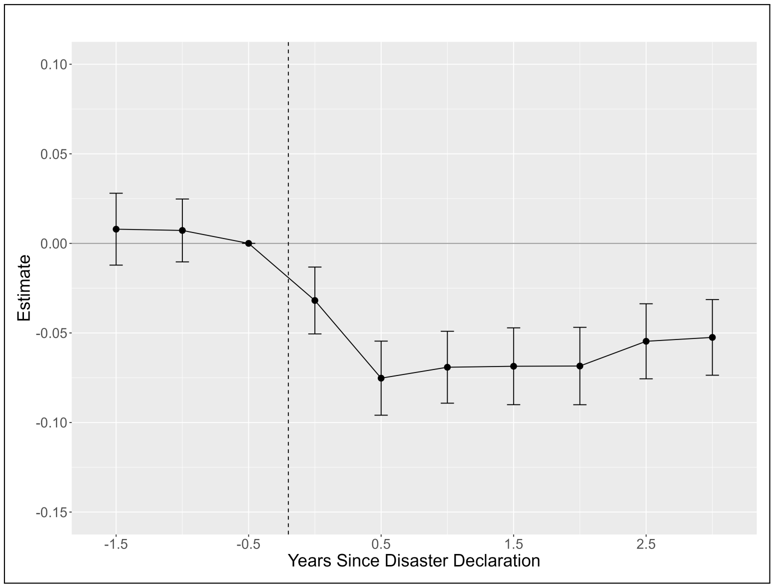
First, Appendix Figure 15 helps clarify that the negative shock of the disaster tends to increase delinquency among both the treated and control populations. Thus, the LATE figures above (Figures 5 and 6) show that loan approval helps stave off these negative effects.

Second, by observing the timing of when delinquency rates deviate between treatment and control groups, we can better understand how households prioritize different payments, the so-called "pecking order" of defaults. We find that credit cards are the first of the three loan types where the high-DTI households' delinquency rates rise faster. This is followed by auto delinquency, and finally mortgage delinquency, consistent with an expectation that households prioritize repaying their mortgage above all other debts. One interpretation of this pecking order is that consumers may be especially averse to foreclosure since it entails a host of consequences (e.g.,

[5] Specifically, $E(amount|delinquent) = E(amount)/P(delinquent) = \$400/0.07 = \$5,714$.

reduction in credit score, possible loss of housing equity, and a requirement to leave a home to which the consumer may be attached, Collier et al., 2021).

Figure 5: Effect of Loan Approval on Likelihood of Delinquency



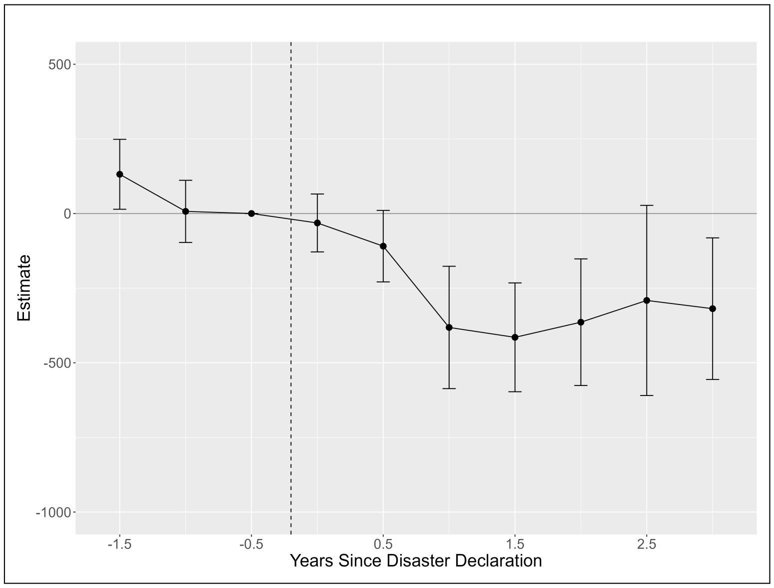
Note: The figure shows the LATE of loan approval on the the likelihood of having any loan 30 or more days late using the DTI threshold as an instrument for approval.

One explanation for this pattern in delinquencies is that the emergency liquidity provided by the disaster recovery loan may help households address their immediate consumption needs, staving off longer term consequences of the disaster. By providing liquidity that allows households to address the needed repairs to their homes, recovery loans may free up household resources to address other consequences of the disaster, such as losing a vehicle.

We examine the number of new auto loans taken by households in the last six months. Figure 8 shows that disaster recovery loan approval causes a 5 pp increase in the share of households that took out a new auto loan in the year following the disaster. This pattern is consistent with a story in which rather than crowding out private borrowing, loan approval appears to loosen credit constraints and stimulate private borrowing.

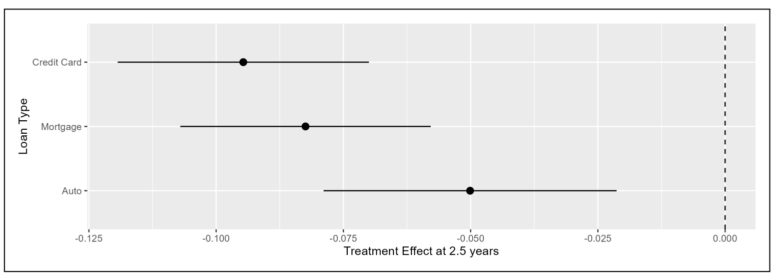
Finally, we investigate whether loan approval allows households to adjust their consumption commitments by moving, and possibly switching from home ownership to renting. In Figure 13 we see that, among those affected, disasters cause big increases in the likelihood of moving (as measured by changing zip codes) and large drops in total private market debt balances stemming

Figure 6: Amount Past Due on Delinquent Loans



Note: The figure shows the LATE of receiving a disaster loan on the amount past due using the DTI threshold as an instrument for approval. The amount past due is the balance that households owe in late loan payments.

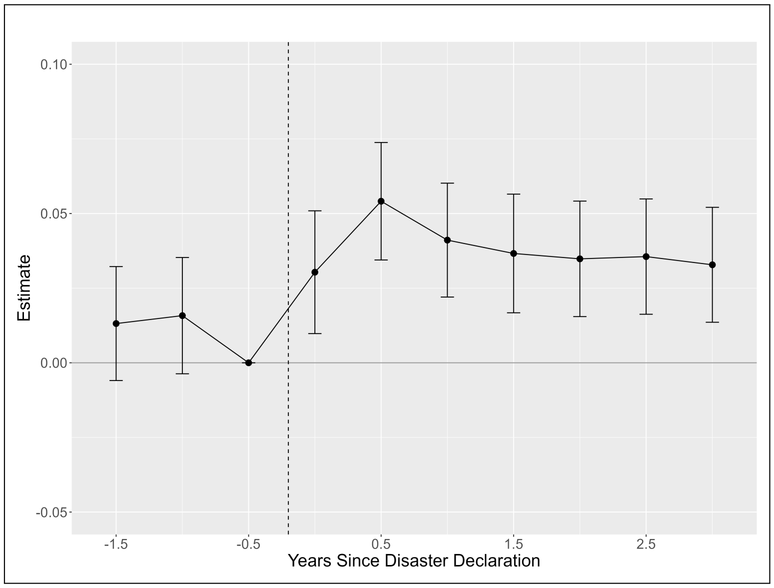
Figure 7: Effect of Loan Approval on Likelihood of Delinquency, by Loan Type



Note: The figure shows the treatment effect of loan approval on the likelihood of having a delinquency for various loan types. The data are restricted to individuals with at least one of each type of loan prior to the disaster, and only include one pre-period (immediately prior to disaster declaration) and one post-period (2.5 years after disaster declaration). The outcome variables are indicator variables for having had a delinquency of a given type in the last 24 months. For each outcome variable y associated with a loan type, the figure displays the β_3 coefficients from the following second stage regression: $y_{itzd} = \beta_0 + \beta_1 POST_t + \beta_2 APRV_i + \beta_3(POST_t X APRV_i) + \gamma_0 DTI_i + \gamma_1(DTI_i \times BELOW_i) + \gamma_2 Z_{zd} + \gamma_3 \tau_{td} + \epsilon_{itzd}$

from becoming less likely to have an open mortgage loan. Appendix Figure 18 shows that these margins of adjustment do not appear to be differentially affected by disaster loan approval.

Figure 8: New Auto Loans



Note: The figure shows the LATE of receiving a disaster loan on new auto loans using the DTI threshold as an instrument for approval. The outcome is the number of new auto loans that households have taken in the last 6 months.

4.3 Heterogeneity Across Households

Next we consider whether the delinquency results exhibit heterogeneity across several pre-disaster dimensions. Our estimates on the full sample may mask important variation in responses to loan receipt, especially if the primary mechanism is through a liquidity channel. Figure 9 plots the mean propensity of having any type of loan delinquency for the 30-40 DTI sample (dashed lines) and the 40-50 DTI sample (solid lines). As applicants with DTI below 40 are more likely to be approved, the plots provide a type of intent-to-treat comparison. The first panel splits the sample by credit score, the second by applicant age, and the third by the share of the applicant's ZIP code that is Black. In each case, the figures show the bottom quartile in red lines and the top quartile in blue lines. The bottom right panel splits the sample by homeowners (red lines) and renters (green lines).

In the top left panel, for households with high credit scores, we see almost no differences at any point in the likelihood of having delinquencies between the low and high DTI groups. In contrast, the lowest credit score quartile household delinquency propensities are almost exactly equal in the year and a half before the disaster, but diverge after the disaster. Post-disaster the higher DTI group experiences a higher delinquency rate than the lower DTI group, rising to a level above their pre-disaster delinquency propensity by one year after the disaster.

In contrast to the heterogeneity in loan approval effects that we see across high and low credit score quartiles, two of the other three plots show roughly similar size gaps opening up between the lower DTI and higher DTI groups post-disaster. Similar sized gaps emerge for older and younger households, and for homeowners and renters. The lower left panel shows a larger gap post-disaster for households living in zipcodes with high Black population shares compared to those living in zipcodes with low Black population shares. While this difference is suggestive of the possibility of a larger effect in neighborhoods with a larger Black population share, we do not have enough power to statistically rule out that the effects are the same size.

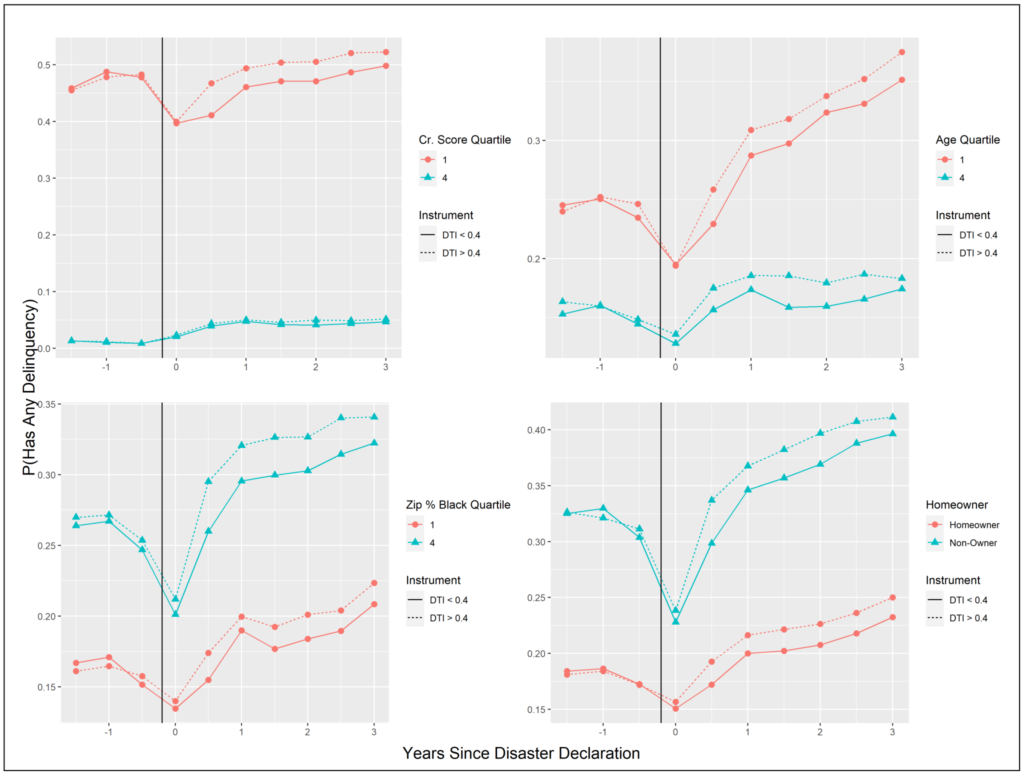
These plots suggest that disaster recovery loans provide similar benefits to a variety of populations. While those applicants with the highest credit scores have the lowest ex-ante delinquency rates, and thus the least room to respond on this margin, we find largely similar benefits of disaster loans for the young and old, homeowners and renters, and across racial groups.

5 Does the Subsidy Matter? Evidence from the Credit Score Discontinuity

Our results thus far show the beneficial impacts of loans following a disaster, but the question remains of whether that benefit is due to a relaxation of liquidity constraints or from wealth effects from the subsidy implicit in the large share of disaster loans which have interest rates set below the market rate. To shed light on the question of liquidity versus wealth effects, we exploit another discontinuous feature of the Federal Disaster Loan program. The probability of receiving a below market rate loan jumps discontinuously as the applicant's credit score falls below 700 points. This credit score discontinuity is useful in providing a situation where borrowers receive similar liquidity benefits on either side of the threshold, but the wealth effect is positive for lower credit score borrowers, and approximately zero for higher credit score borrowers. Furthermore, it provides a particularly unique setting in which loan pricing is higher for lower risk borrowers, contrary to standard practices of risk-based pricing.

Figure 10 presents the relationship between whether a household received a below-market rate disaster loan offer and their credit score at the time of application. The sample comprises all disasters from 2006-2013, when this discontinuous pricing policy was in use. The effect of having a

Figure 9: Heterogeneity

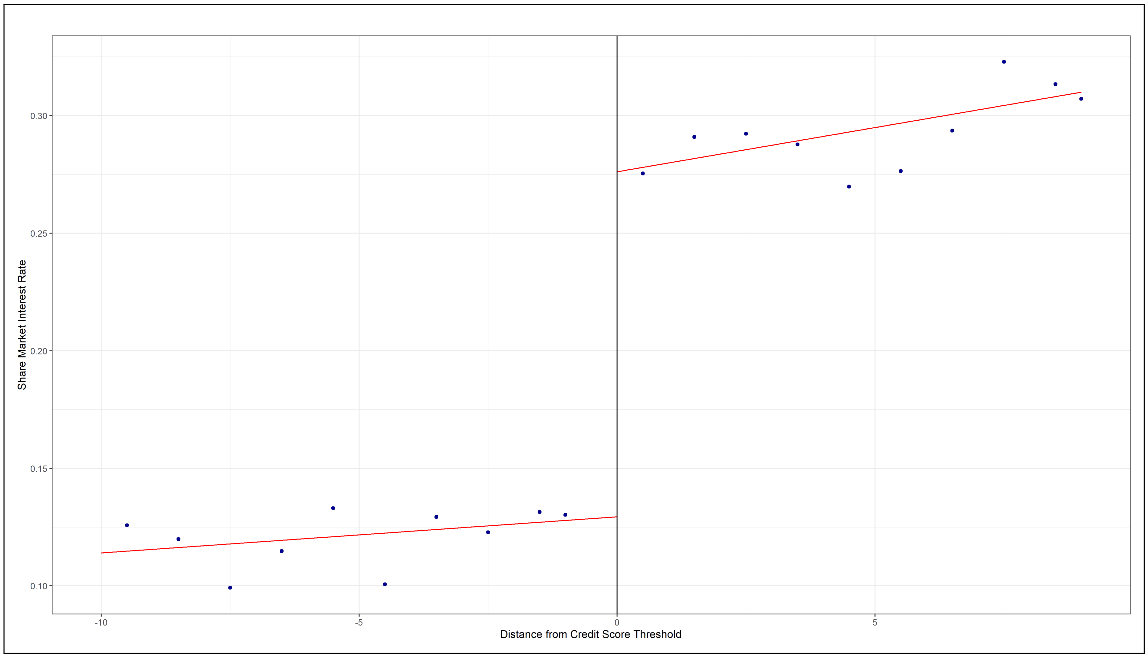


Note: The figure shows heterogeneity in the evolution of raw means of the propensity of having any type of loan delinquency over time. Solid lines plot means for the sample of people with a DTI between 0.3 and 0.4 as of loan application. Dashed lines plot means for people with a DTI between 0.4 and 0.5. Heterogeneity in effects are shown by comparing the first and fourth quartile of applicants by credit score (upper left), age (upper right), and Black population share of zip code (lower left). The lower right panel shows heterogeneity across homeowners and renters.

credit score over the 700 threshold sharply increases the probability of receiving a market interest rate by roughly 10 percentage points.

Figure 11 shows the effect of receiving a loan offer with a market interest rate on the probability of having any type of loan delinquency, relative to receiving a loan offer with a subsidized interest rate . In all our specifications, we find no statistically significant effect of receiving a higher interest rate loan offer on the likelihood of delinquency except in the period between 2 and 2.5 years after the disaster. However, the higher rate *reduces* the probability of having a loan that is past due - the opposite direction of what one would expect from the wealth effect of the subsidy. Appendix Figure 22 shows similar estimates for the effect of receiving a loan offer with a market interest rate on the dollar amount that is past due. Our estimates imply that the higher interest rate shows no evidence of increasing the dollar amount that is past due.

Figure 10: Change in Below-Market Rate Likelihood at the Credit Score Threshold



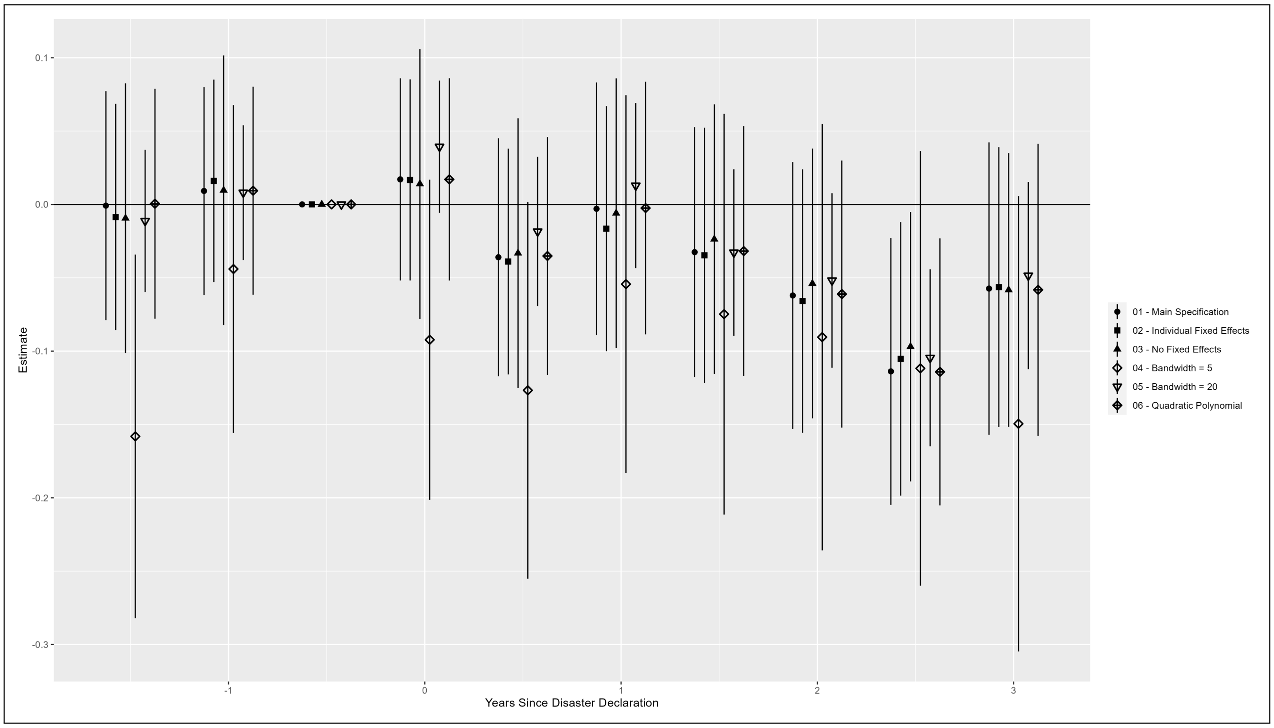
Note: The figure shows the discontinuous change in the likelihood of being offered an unsubsidized loan rate loan for households above the credit score threshold of 700 relative to households below the threshold.

Overall, the evidence from the credit score discontinuity supports the view that receiving a subsidized loan offer does not have a significant beneficial effect in terms of reducing the dollar amount of debt that is past due or the probability of having a delinquent loan. This result suggests that wealth effects are not playing an important role in the beneficial effects of receiving a loan offer. This finding reflects a local average treatment effect for the population around the 700 FICO score cutoff, which may be a more positively-selected group than the group around the 40 percent DTI cutoff. The combined evidence from the DTI and FICO score discontinuities suggest that the main driver of delinquency reduction comes through the liquidity provision of the loan, as opposed to the wealth effect of a subsidized loan.

6 Robustness

In this section, we examine the results under a variety of alternative specifications of the baseline estimating equation. Figure 12 shows how the effect of loan approval on the likelihood of bankruptcy varies across models. The first plot repeats our preferred estimation strategy for reference. The next plots adjust the model fixed effects and controls. We then winsorize the outcome.

Figure 11: Effect of Market Interest Rate Loan on Likelihood of Delinquency

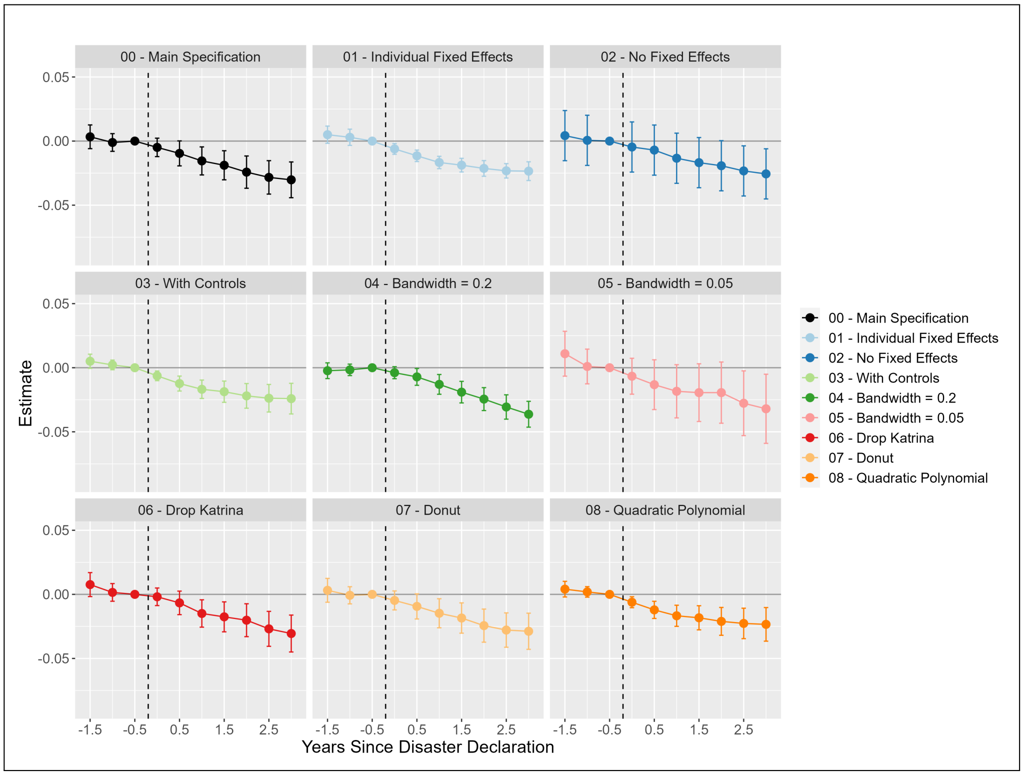


Note: The figure shows the LATE of receiving a market interest rate disaster loan on the likelihood of having an account past due. The credit score threshold of 700 is used as the instrument for receiving a market rate versus a lower interest rate loan.

Next, we vary the baseline DTI bandwidth (10 pp) by expanding it to 20 pp and reducing it to 5 pp. The next plot omits the largest event in the data, Hurricane Katrina. The "donut" plot omits observations just above and below the DTI threshold out of concern that some incentive to manipulate the data may exist at the threshold. The preferred model includes linear controls for the running variable (DTI); in the final plots we additionally examine quadratic and cubic controls for the DTI ratio.

Across specifications, the results appear quite robust. Loan approval reduces the likelihood of bankruptcy by around 2 pp, though the exact timing and magnitude are influenced by the specification. In Appendix D, we similarly examine alternative specifications for modeling the effect of loan approval on households' amount past due on delinquent loans and on households' take-up of new auto loans. In both cases, our main findings appear consistent across a variety of specifications.

Figure 12: Effects of Loan Approval on Bankruptcy, Alternative Specifications



Note: The figure shows the LATE of loan approval on the likelihood of having a bankruptcy on their credit report. The series of plots show how alternative specifications of the estimating equation affect the results.

7 Complementary Evidence on the Costs of Disasters

In this section, we provide two dimensions of descriptive evidence around the costs of experiencing a natural disaster. These offer additional context that is useful for understanding our results. We first examine credit market outcomes around the disaster date, showing persistent adverse effects of the disaster. Second, we explore responses to a survey of households managing their disaster repairs. The survey sheds light on a broader set of recovery strategies than can be observed on consumers' credit reports (e.g., using savings, delaying medical care).

7.1 Evidence from Credit Records

To examine the balance sheet consequences of natural disasters, we compare credit market outcomes of households that have experienced a disaster with a random sample of U.S. credit records, drawn outside of exposed communities, at the same point in time. Specifically, the disaster-affected households are applicants to the FDL program. These households provide an opportunity to assess how uninsured disaster losses affect consumers' finances. A challenge for existing studies is that the authors can measure flood depths but cannot assess the extent of households' financial losses (e.g., Gallagher and Hartley, 2017; Billings et al., 2021). As that literature notes, a number of factors intermediate the relationship between flooding and financial losses — topography, home elevation, insurance coverage, etc. These factors make flood depths a type of intent-to-treat measure, likely attenuating the true effect of flood losses on households' balance sheets. We look at the evolution of credit record outcomes in an event study framework, where the event is the date of the disaster.[6]

Figure 13 plots event study coefficients on time relative to experiencing a disaster. The figure follows consumers from two years before to seven years after the disaster, with each point representing six months. The top left panel traces out the total private market debt balance (which does not include Federal Disaster Loans) of affected households after a disaster, showing a sharp drop in total reported debts. This result can largely be attributed to the closing of mortgage accounts (top right) and a large increase in moving, defined by switching zip codes (middle left). In short, total outstanding debt falls because homeowners sell their homes and move elsewhere as renters. Those homeowners who stay ultimately have more trouble paying their mortgages, as shown in the middle right panel. Households replace cars at a higher rate after a disaster (bottom right), likely due to direct damage of property.

Examining financial distress, we find that the total amount past due falls temporarily, possibly due to extended forbearance options in the wake of the disaster, but rises steadily thereafter (bottom left). The credit market picture for those that experienced a natural disaster is one in which there is higher mortgage delinquency and greater amounts past due, starting around two years after the disaster and continuing to the end of the time series. We take this as new evidence that direct exposure to natural disasters creates long-term persistent financial challenges.

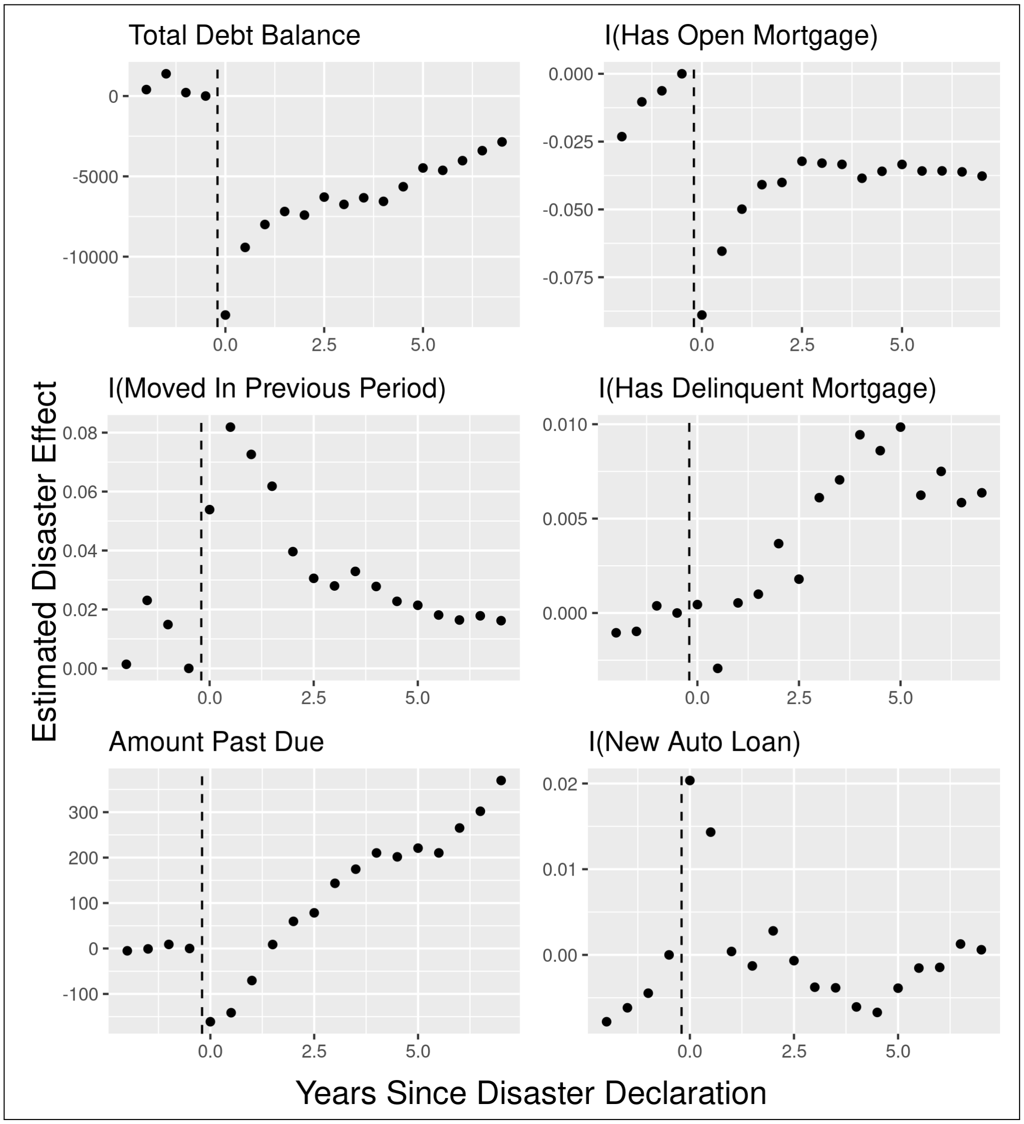
7.2 Evidence from a Survey of Household Recovery Funding

To understand how households manage disaster repairs, we obtained data from a survey conducted by the Wharton Risk Center. The survey includes 474 respondents who incurred damage to their home from one of four major hurricanes between 2017 and 2021.[7] The top panel of Table 2

[6] Specifications with additional controls are qualitatively similar and are available upon request.

[7] The studied events are Hurricane Harvey (n = 136), Hurricane Florence (n = 117), Hurricane Michael (n = 96), and Hurricane Ida (n = 125). The survey was primarily distributed through Qualtrics, which randomly sampled individ-

Figure 13: Credit Market Consequences of a Disaster



Note: The figure shows point estimates of coefficients on event time indicators comparing disaster-affected households to a nationally representative sample of people drawn from outside of the disaster-affected area at the same point in time.

shows how households funded damages to their homes from these disasters. The categories are not mutually exclusive and show that consumers often fund repairs through multiple sources.

uals in its internet panels who lived in disaster-affected areas. The survey was additionally distributed through (1) a geographically targeted Facebook ad campaign, (2) spots on local radio stations, and (3) community group outreach. Only individuals affected by the hurricane and who are the primary decision-maker in their household are included in the table. Participants were entered in a lottery to win gift cards valued at $20-30. See You and Kousky (2022) for additional details regarding data collection and results. We thank these authors and the Wharton Risk Center for use of the data.

Over half of respondents used homeowners or renters insurance to fund repairs. These insurance products do not cover flood risks but often address hurricane-related wind damages. Many consumers, even those in very vulnerable locations, do not buy flood insurance (Walsh, 2017). Consistent with this pattern of low flood-insurance take-up, only 21% of respondents received flood insurance claims payments.[8] Half of respondents also reported drawing down savings to fund repairs. This savings drawdown aligns with Deryugina et al. (2018), who find that Hurricane Katrina significantly increased early withdrawals from individual retirement accounts.

Among consumers using credit, the most frequently used option is credit cards, with a fifth of respondents saying they turned to revolving credit. Note that some credit card use may represent short-term, low-cost borrowing: del Valle et al. (2022) find that households affected by Harvey open new credit cards at promotional rates and then pay off these balances before the promotion expires. The median credit card in their analysis has a $3,000 limit, suggesting an inability to fund large repairs in this way. However, for other households, credit card usage may reflect borrowing at a high cost to fund repairs. For example, Morse (2011) and Dobridge (2018) find that disasters also increase payday loan borrowing. Regarding long-term loans, 8% of respondents funded repairs using a loan from a private lender, while 7% received a Federal Disaster Loan. The results may also reflect consumers' inability to garner a loan and/or their reluctance to fund repairs through long-term borrowing.

The second most common category of funding source was transfers from family and friends, governments, non-profits, or employers. Twenty-nine percent of respondents received assistance from family and friends, while 19% percent of respondents received a FEMA grant. These grants are typically small, averaging $4,500 during our period of study. Ten percent or fewer of respondents received assistance from a charitable organization or an employer or a local government.

As a result of the disaster, households adjusted not only their balance sheet through drawing down savings and increasing their debt, but also shifted their consumption and work behavior. The bottom panel of Table 2 shows how survey respondents adjusted to address the costs of repairs: 40% reduced their spending on consumer goods, 16% spent less on medical care, and 20% report (likely temporarily) moving in with family or friends. 29% of respondents took on additional work to cover incurred costs. A common reaction to disaster-imposed costs is to delay payments on existing obligations, with 27% falling behind on utility bills, 24% on credit card bills, and 18% on housing (rent or mortgage) expenses.

[8]Additionally, coverage limits from the National Flood Insurance program is capped at $250,000 for the structure and $100,000 for its contents. As a result, even households with flood insurance may be partially insured against flood damages so may need to supplement insurance claims payments with other funding sources.

Taken together, the results from the survey suggest that disasters drain savings and force households to make adjustments on many margins, including borrowing, consumption, taking on additional work, and delaying payment obligations. Disasters not only lead many to fall behind on payments directly, a form of financial distress, but also put others on the verge of distress by drawing down emergency savings.

Table 2: Funding Disaster Repairs

Funding source	%
Savings	51
Insurance	
Homeowners/Renters Insurance	54
Flood Insurance	21
Credit	
Credit cards	19
Formal loan from private bank or lender	8
Federal disaster loan	7
Transfers	
Family & friends	29
FEMA grant	19
Charity, nonprofit, or community group	10
Employer	8
Local government	5
Action taken	**%**
Took on extra work	29
Delayed payments	
Fell behind on utility bills	27
Fell behind on credit card bills	24
Fell behind on rent/mortgage	18
Reduced consumption	
Spent less on consumer goods	40
Spent less on medical care	16
Spent less on education	6
Moved in with family or friends	20
Sold personal belongings	19
None of the above	28

Note: Table presents survey responses from the following questions, (1) "Which of the following sources provided funds to help pay for the costs of repairing/rebuilding your home or for the costs of replacing items inside your home? (check all that apply)" and (2) "did you or anyone in your household do any of the following to pay for costs incurred as a result of [Event Name]? (check all that apply)."

8 Conclusion

What is the causal effect of credit receipt on households' balance sheets? We answer this question in the context of emergency credit provision after natural disasters. Using consumer credit reports, we track the borrowing and repayment behavior of a large group of applicants to a federal program that offers low-interest disaster recovery loans. The program's use of an arbitrary rule-of-thumb around 40% DTI provides a source of exogenous variation for comparing similar applicants, some of whom are differentially more likely to receive the recovery loan, thus isolating the causal effect of credit provision.

We find large and persistent positive effects of emergency credit provision. Loan receipt reduces the likelihood of credit delinquency and bankruptcy following the disaster, even 3.5 years after the event. Emergency credit also appears to crowd-in private-sector borrowing for real outlays including new vehicle purchases. In summary, our findings suggest that well-timed liquidity provision can stem the consequences of a negative shock, offering significant and lasting benefits to affected households.

Our results have important implications for understanding household consumption and debt usage patterns. Households' disaster expenses on top of existing financial obligations appear to drive many who do not receive the loan into financial distress. In contrast, those who receive liquidity are able to catch up on their bills in the short-term, avoid the worst outcomes like severe delinquency and bankruptcy, and ultimately save a downpayment for a new car purchase. These results suggest that adjusting consumption commitments is challenging and that the financial strain of expense shocks are not easily smoothed over time by those with impaired credit ex ante.

Our work also informs how best to aid households in a crisis. We find that short-term liquidity provided by the government reduces household financial distress in ways that private credit markets fail to replicate. Those denied disaster loans do not use private credit markets such as credit cards to solve these substantial liquidity needs. The lack of private credit provision, due to adverse selection or other drivers, suggests an important role for public credit markets to play in times of need. Comparing those who receive a subsidized interest rate with those who do not, we find that the benefits are due to liquidity rather than the subsidy. Thus, credit-based aid programs facing a trade-off on the extensive vs. intensive margin of lending should carefully consider the cost of subsidizing the price of credit at the expense of helping fewer at-risk households.

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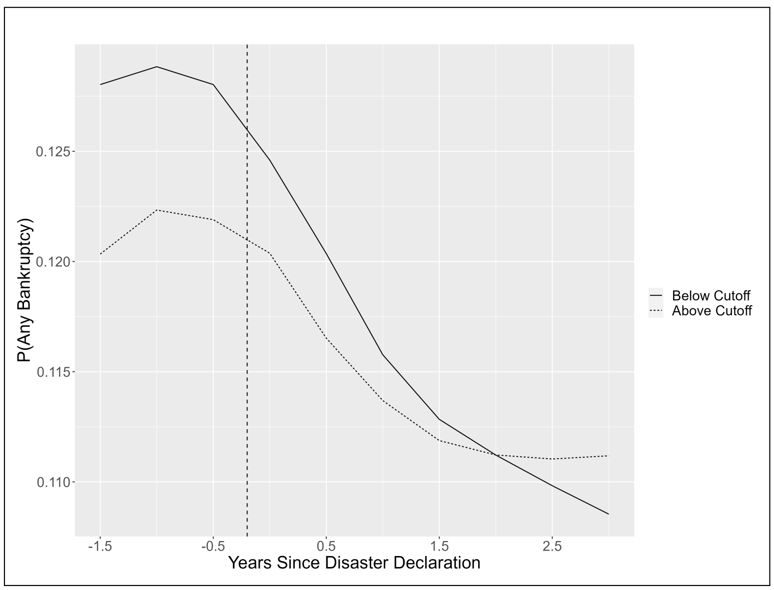
Online Appendix A Summary Statistics, Analysis Sample

Table A1 presents summary statistics for our analysis sample for just under 60,000 applicants with DTI between 30 and 50 percent in our sample. The top panel pools all applicants while the middle and bottom panels split the sample based on the 40 percent DTI threshold. Comparing the means of all variables except income and DTI reveals economically small differences between the two groups. Of course the differences in DTI simply reflect the split of the sample. The differences in income are somewhat mechanically related to this split as well since income is in the denominator of DTI.

Online Appendix B Level-Plots of Key Outcomes

Figure 14: Likelihood of Bankruptcy



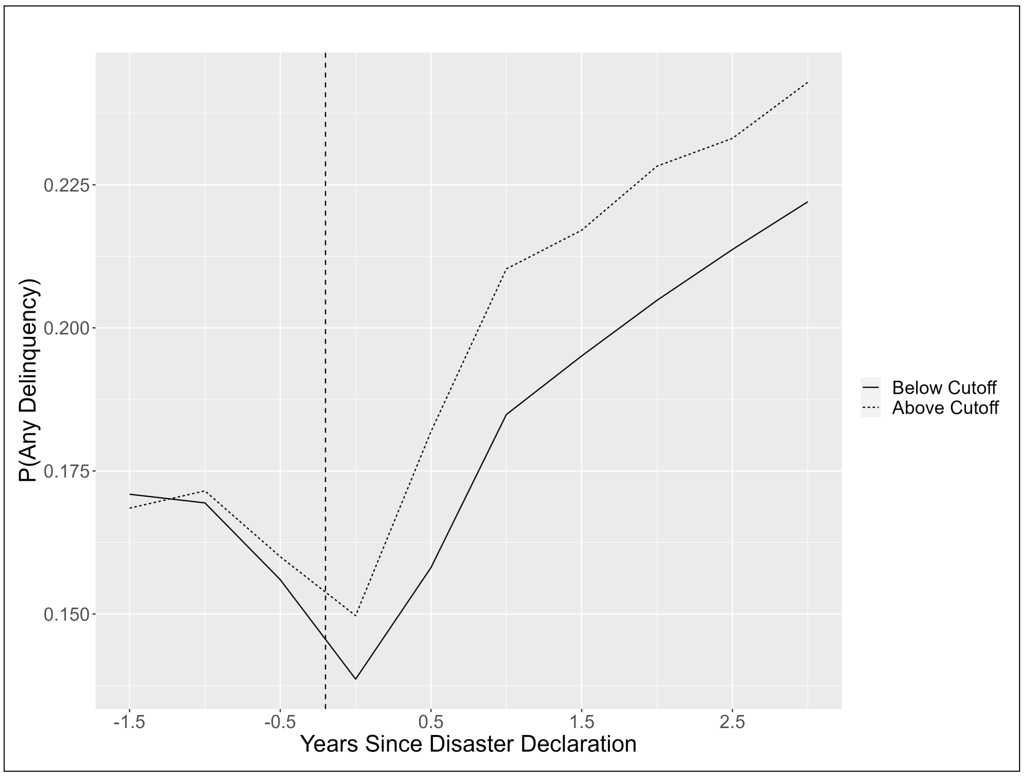
Note: The figure shows the share of households with a bankruptcy on their credit report for two groups based on debt-to-income at loan application. The solid line represents households with DTI below the threshold, who are significantly more likely to be approved for a disaster loan compared to those above the DTI threshold (dashed line).

Table A1: Summary Statistics of Analysis Sample

	Mean	SD	Percentiles p10	p50	p90
Analysis Sample					
Income	55244	38244	19332	45247	102000
Credit Score	659	82	556	653	780
DTI	0.38	0.06	0.31	0.38	0.47
Loss Amount	72024	82467	9500	39000	184077
Indicator for Any Delinquent Loan	0.21	0.40	0.00	0.00	1.00
Amount Past Due on Delinquent Loans	300	2497	0	0	80
Indicator for Recent Bankruptcy	0.03	0.17	0.00	0.00	0.00
Number of New Auto Loans	0.10	0.31	0.00	0.00	0.00
Income	56496	38454	20600	46643	103103
Credit Score	659	83	556	653	780
DTI	0.38	0.06	0.32	0.38	0.47
Loss Amount	73418	83290	9755	39934	186497
Indicator for Any Delinquent Loan	0.20	0.40	0.00	0.00	1.00
Amount Past Due on Delinquent Loans	282	2375	0	0	76
Indicator for Bankruptcy	0.13	0.33	0.00	0.00	1.00
Number of New Auto Loans	0.10	0.32	0.00	0.00	0.00
Analysis Sample, DTI $<$ 40					
Income	59475	39884	21950	49500	107667
Credit Score	660	83	556	654	781
DTI	0.35	0.03	0.31	0.35	0.39
Loss Amount	75105	85113	9981	40685	189677
Indicator for Any Delinquent Loan	0.20	0.40	0.00	0.00	1.00
Amount Past Due on Delinquent Loans	269	2308	0	0	66
Indicator for Bankruptcy	0.13	0.34	0.00	0.00	1.00
Number of New Auto Loans	0.10	0.31	0.00	0.00	0.00
Analysis Sample, DTI $\geq$ 40					
Income	51557	35409	18717	41925	95527
Credit Score	657	81	556	651	776
DTI	0.45	0.03	0.41	0.44	0.49
Loss Amount	70620	80098	9396	38593	181659
Indicator for Any Delinquent Loan	0.20	0.40	0.00	0.00	1.00
Amount Past Due on Delinquent Loans	304	2483	0	0	90
Indicator for Bankruptcy	0.12	0.33	0.00	0.00	1.00
Number of New Auto Loans	0.10	0.32	0.00	0.00	0.00

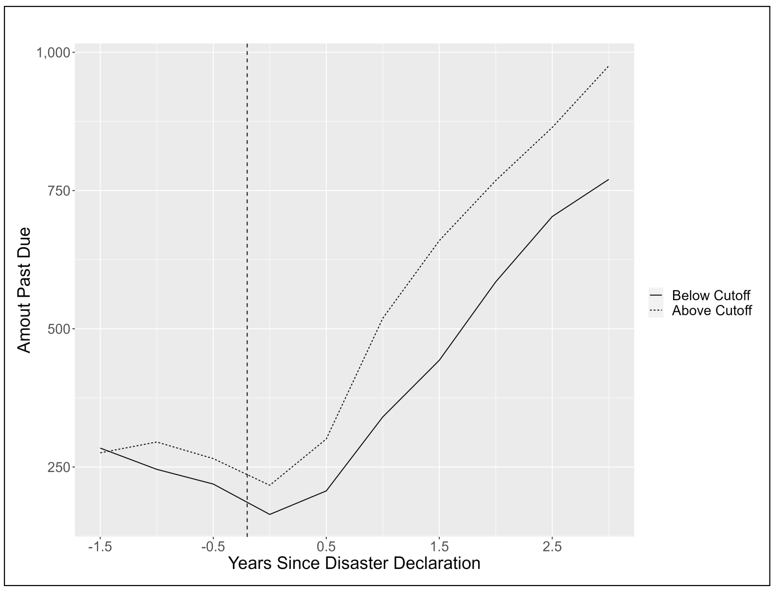
Note: Table includes data on 59,336 applicants with debt-to-income ratios between 0.3 and 0.5. See Table 1 note for details on variable definitions.

Figure 15: Conditional Means, Delinquencies



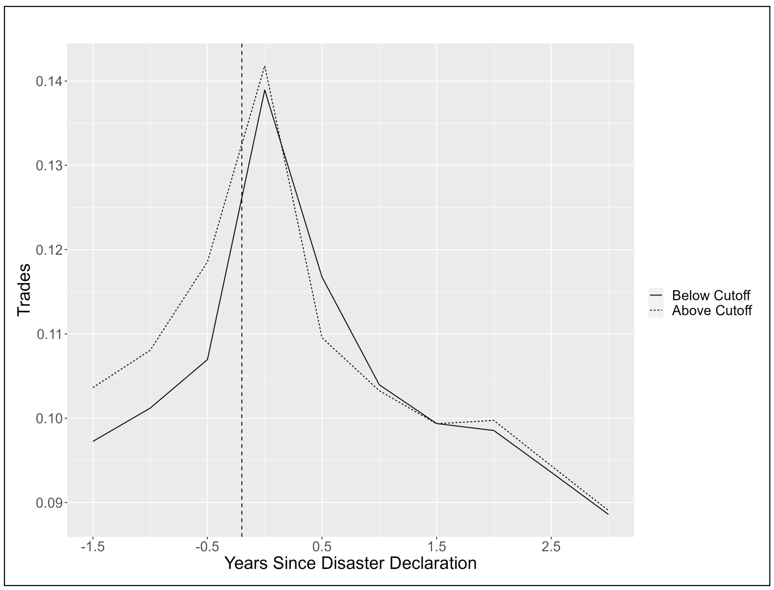
Note: The figure shows the share of households with any loan delinquent by 30 or more days, for two groups based on debt-to-income at loan application. The solid line represents households with DTI below the threshold, who are significantly more likely to be approved for a disaster loan compared to those above the DTI threshold (dashed line).

Figure 16: Amount Past Due on Delinquent Loans



Note: The figure shows the amount that households owe in late loan payments, for two groups based on debt-to-income at loan application. The solid line represents households with DTI below the threshold, who are significantly more likely to be approved for a disaster loan compared to those above the DTI threshold (dashed line).

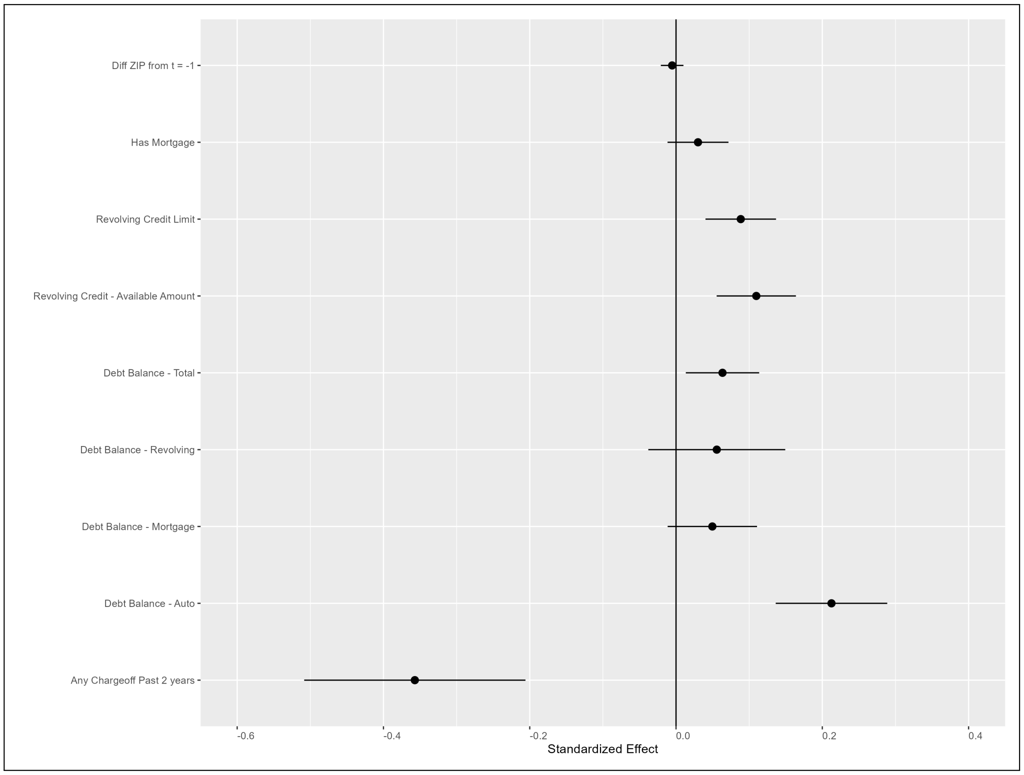
Figure 17: New Auto Loans



Note: The figure shows the number of new auto loans that households have taken in the last 6 months, for two groups based on debt-to-income at loan application. The solid line represents households with DTI below the threshold, who are significantly more likely to be approved for a disaster loan compared to those above the DTI threshold (dashed line).

Online Appendix C Event Study Plots of Other Outcomes

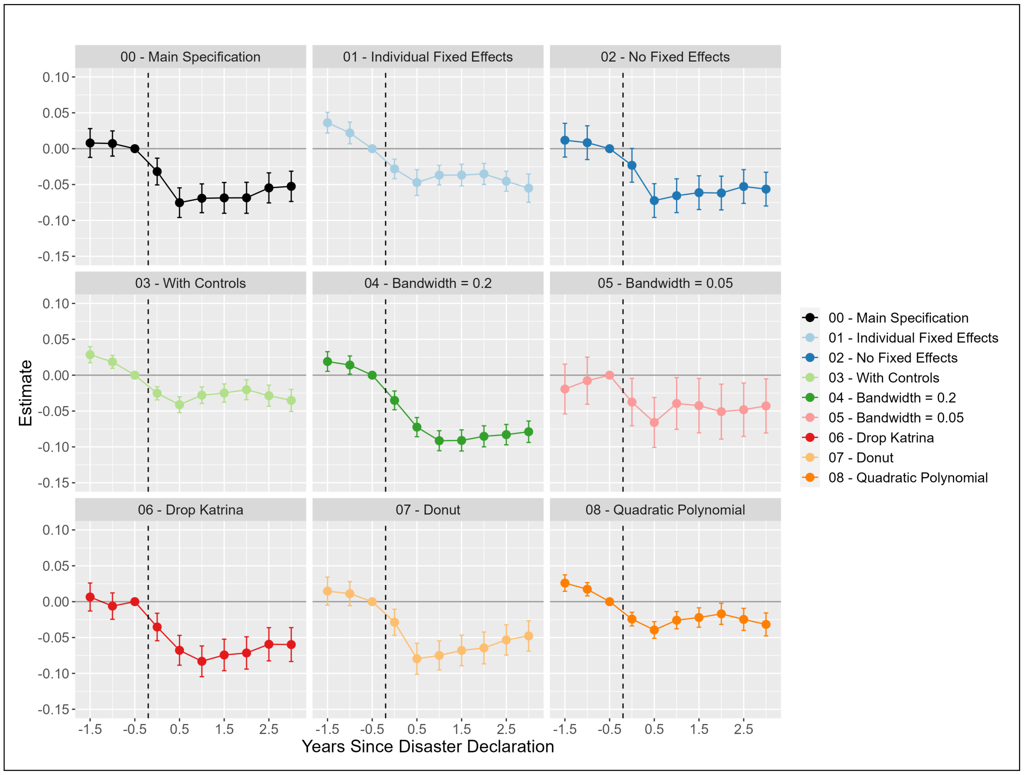
Figure 18: Effect of Loan Approval on Other Outcomes - Event Study



Note: The figure shows the treatment effect of loan approval on various outcomes 2.5 years after the disaster: the propensity to have moved to a different ZIP code from prior to the disaster, the propensity to have a mortgage account, total private market debt balances, and the propensity to have any chargeoff in the past two years.

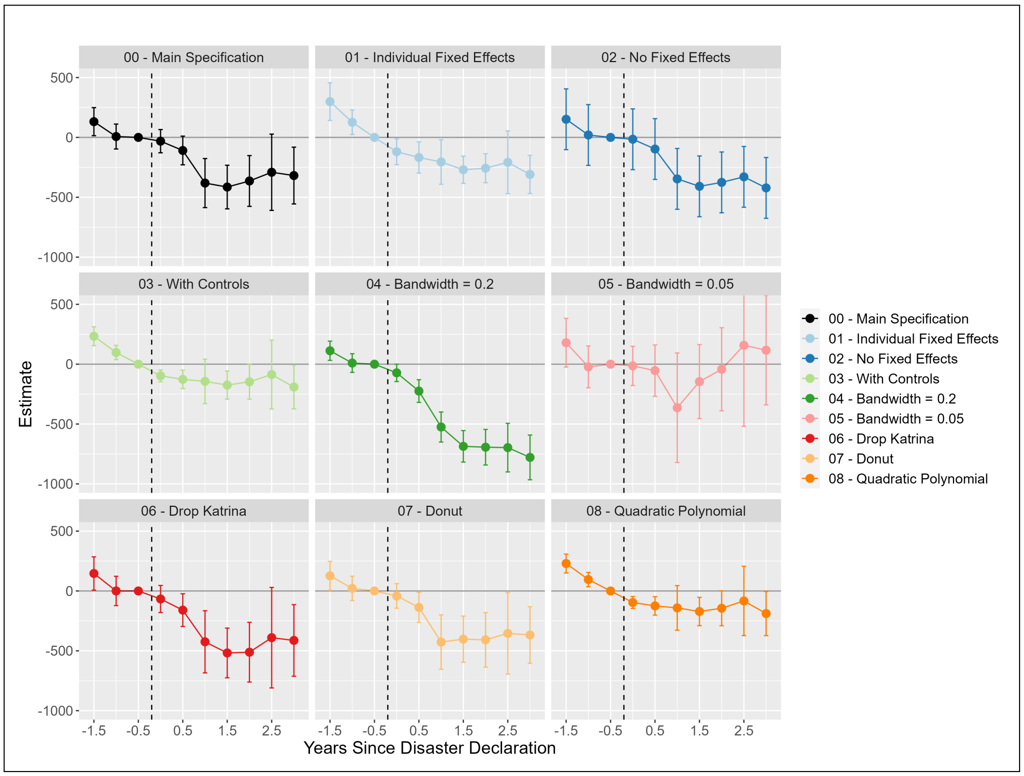
Online Appendix D Additional Robustness Results

Figure 19: Effects of Loan Approval on Delinquency, Alternative Specifications



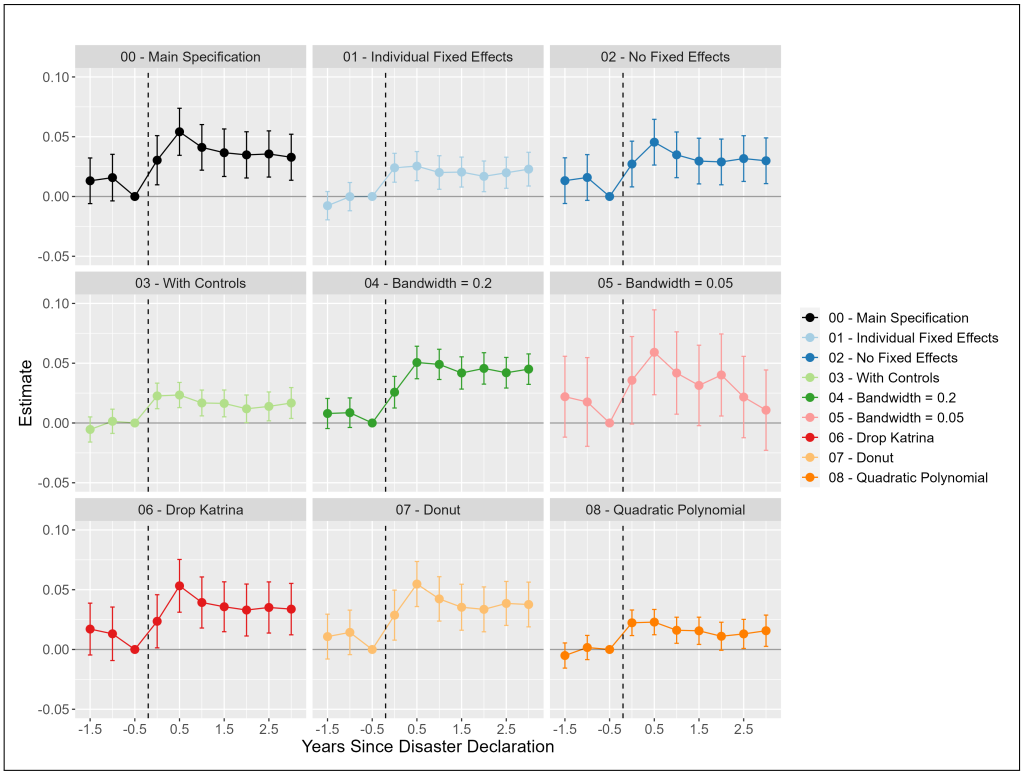
Note: The figure shows the LATE of loan approval on the likelihood of having any loan 30 or more days late. The series of plots show how alternative specifications of the estimating equation affect the results.

Figure 20: Effects of Loan Approval on Amount Past Due, Alternative Specifications



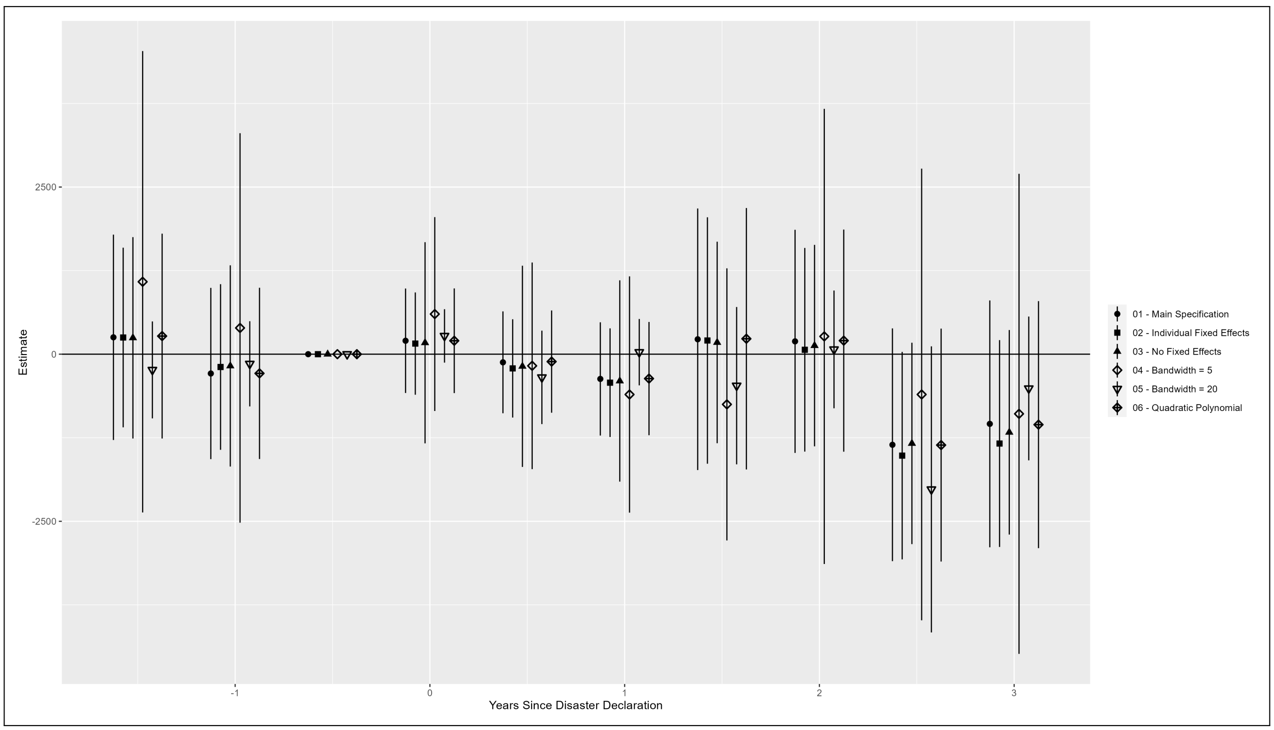
Note: The figure shows the LATE of loan approval on the amount past due on delinquent loans. The series of plots show how alternative specifications of the estimating equation affect the results.

Figure 21: Effects of Loan Approval on New Auto Loans, Alternative Specifications



Note: The figure shows the LATE of loan approval on the number of new auto loans that households have taken in the last 6 months. The series of plots show how alternative specifications of the estimating equation affect the results.

Figure 22: Effect of Market Interest Rate Loan on Amount Past Due



Note: The figure shows the LATE of receiving a market interest rate disaster loan on the dollar amount that is past due using the credit score threshold of 700 as an instrument for getting a market rate versus a lower interest rate loan.