After the Storm: Direct and Spillover Benefits from Disaster Loans to Small Businesses

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Abstract

The increasing frequency and severity of natural disasters creates new imperatives to identify efficient and effective policies to aid recovery in the aftermath. One of the largest and longest running such programs globally is the U.S. disaster loan program, which offers businesses loans to repair physical damage following a disaster. This rapid injection of capital could catalyze firm survival and growth, with implications for the local community. However, more debt might not be helpful: The loans increase firm risk and come with an interest burden, could prop up "zombie" firms that should exit, and may crowd out private capital. We evaluate the causal effect of disaster loans using comprehensive administrative data tied to both financial and real outcomes between 2004 and 2020. Receiving a disaster loan has strong and persistent positive effects, reducing the chances of firm exit and increasing employment and revenue. The loans unlock additional, non-SBA private credit while also reducing delinquency and bankruptcy. The loans are more useful for firms and places that are more constrained and have more vulnerable populations. Finally, we find evidence of positive spillovers on the firm entry margin, but suggestive evidence of negative spillovers on incumbent neighbor firms. Overall, the loans appear to strongly benefit recipient firms and likely benefit the local economy as well.

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1 Introduction

The costs of severe climate events are growing. In the 1980s, 31 natural disasters in the U.S. each exceeded $1 billion in damages; in the last decade, 151 billion-dollar disaster occurred (in 2022$; NOAA, 2022). National governments frequently step in to facilitate reinvestment in affected communities. A primary policy tool is to provide businesses with subsidized disaster recovery loans intended to help businesses replace damaged physical capital; this approach is used by governments in Australia, Canada, Japan, and the U.S., among other countries.[1] The hope is that disaster loans help businesses regain productivity, spurring local economic recovery.

Yet despite their widespread use and increasing importance, the extent to which disaster loans contribute to business recovery is unclear. By providing liquidity, recovery loans may enable businesses to repair productive assets and fulfill immediate obligations, facilitating recovery by staving off financial delinquency and forced exit. In turn, healthy businesses may contribute to local economic recovery by creating jobs and expanding tax revenues. Their success may also spill over to neighbors, for example by bringing foot traffic to retailers nearby.

Alternatively, by increasing firm leverage, recovery loans might instead increase the chance of firm failure in the years ahead. Furthermore, recovery loan programs could hinder efficient market forces. On the one hand, they may prop up "zombie" firms that should fail in the creative destruction process, which the disaster might otherwise hasten. On the other hand, they may crowd out private investment if they are allocated only to high-quality firms that can attract private capital regardless. In either case, the loans would likely contribute little to local economic recovery, making the program a poor use of taxpayer resources.

In this paper, we offer the first causal examination of how government-provided disaster recovery loans affect recipient firms and their local business communities. We assess U.S. Small Business Administration (SBA) disaster recovery loans, using comprehensive data on applications, approval processes, and loans between 2005 and 2017. These loans, which are underwritten, originated, and serviced by the SBA directly, are the only form of U.S. federal disaster assistance provided directly to firms. They are disbursed to businesses that have been adversely affected by a natural disaster, and are primarily intended to repair damaged property. During our period of study, 167,000 unique firms applied for a disaster loan, and ultimately, the SBA provided $5.3 billion in loans to 54,500 firms. The borrowers collectively have over 230,000 employees at the time of application. In addition to basic information about firm demographics, the SBA data include lending decision inputs and loan terms.

[1]See NSW (2022), CMHC (2022), Public Safety Canada (2022), Japanese Finance Corporation (2022), and S.B.A. (2022). Countries also began or expanded business recovery lending during the COVID-19 pandemic including Germany (Kfw, 2020), Italy (MEF, 2020), the Netherlands (Government of the Netherlands, 2020), the U.K. (gov.uk, 2020), and the U.S. (SBA, 2022).

One advantage of our study is to observe both financial and real economic outcomes. We link loan applications to data from the U.S. Census Bureau and to business credit reports from Experian. In the U.S. Census Bureau data, we observe the real outcomes of firm exit, transition from employer to nonemployer firm (which we call "deformalization"), employment, and revenue. From the Experian credit reports, we draw private (non-SBA) debt balances, credit delinquencies, all contracts (a holistic measure which includes leases, utilities and telecom contracts, etc.), and firm bankruptcy. For each real or financial outcome, we observe an annual panel of approved and declined disaster loan applicants, which we track from five years before to seven years after the firm experienced a natural disaster. To assess local spillovers, we also collect the credit reports and Census records for the neighbors of recovery loan applicants.

To causally estimate the effects of disaster loans, we leverage discontinuities in the the loan approval process. The likelihood of approval jumps discretely based on the FICO score of the business owner.[2] The program has employed various target FICO scores over time. Searching across the FICO distribution in our application data, we find 22 statistically and economically significant FICO-based approval thresholds across disasters, following the approach in Argyle et al. (2020). Combined, the program used these thresholds to make lending decisions for 916 distinct natural disasters. The 22 natural experiments enable an instrumental variables, difference-in-differences (IV-DiD) design. In the first stage, we instrument for approval using the FICO threshold, with a bandwidth of 29 FICO points around each threshold (the results are robust to alternative bandwidths). In the second stage, we examine how instrumented approval affects business outcomes over time. Firm characteristics are smooth through the FICO thresholds, there is no evidence of pre-trends in the IV-DiDs, and there is no evidence of bunching in a test of applicant density around the cutoff. These results support interpreting the natural experiments as effectively randomly assigning credit to businesses around the owner-FICO threshold, enabling local average treatment effect (LATE) estimates. The FICO thresholds range from 540 to 720, allowing us to examine the effect of a recovery loan on a much broader group of businesses than a single discontinuity would allow.

The disaster recovery loans have strong, positive effects on real outcomes. We first consider exit; natural disasters greatly increase the likelihood of exit. For example, FEMA reports that 25% of affected firms close permanently after a disaster.[3] In our data, the recovery loans reduce the likelihood of firm exit by 13 percentage points (pp), which is 115% of the sample mean. Relatedly, they reduce the chances of deformalization by 5 pp, or 85% of the mean. Reorganizing the firm to deformalize indicates a transition away from a growth mindset, with implications for future hiring. The effects on exit and deformalization grow over time, with the largest magnitudes in the sixth and seventh years after the event. This persistence—even after borrowers have been servicing their disaster loans for several years—reduces concerns that survival effects are driven

[2] For example in 2014, an applying business with an owner FICO of 640 is 16 percentage points more likely to be approved than an applicant with a 630.

[3] See here.

by temporary delays in exit for zombie firms. Instead, the persistent effect indicates that the disaster loan placed firms on a different path, permanently reducing the likelihood of exit from the disaster.

Especially among employer firms, we find large effects of the disaster loan on firm employment and revenue. In the full sample, a loan increases employment by 18%, which represents about $\frac{1}{2}$ of a worker. In the employer sample, the effect is 45%, representing about five workers. For employer firms, we also find significant increases in revenues, around 200% of the mean. As employer firms are central to economic growth (Haltiwanger, 2022), these effects are especially important for local economic recovery.

Next, we turn to the financial side. The SBA disaster loans lead to dramatically more non-SBA private debt; specifically, they increase balances by $18,000 on average, which is 200% of the mean. This positive treatment effect on balances begins just following the disaster and is strongest five years after the shock. We similarly find that SBA disaster loans increase the total number of contracts in which the firm engages (including loans, leases, utilities and telecom contracts). These results indicate that disaster loans are crowding *in*, not crowding out, private credit. SBA borrowers are able to recover sufficiently to make additional financial commitments and to attract private investors. Through repairing physical capital, disaster loans may help firms to recover productivity, restore the quality of collateral, or serve as a signal of firm quality to private lenders.

We can also observe firms' ability to fulfill their debt obligations. After the disaster, we see higher rates of bankruptcy filings, more days late in payment on all contracts, and more delinquencies among both approved and declined firms. However, these increases are much smaller for approved firms. The causal estimates find that disaster loans reduce bankruptcy filings by around 3.8 pp, over 100% of the mean. Combining Census data on firm exits and Experian credit reports, we show that among employer firms, there is a much stronger effect on exit with bankruptcy than on exit with delinquencies or exit with no evidence of adverse financial outcomes. Reducing bankruptcies appears especially valuable as bankruptcy filing is costly and transfers a portion of the costs of exit to the firm's lenders and other liability holders. Consistent with the observed effects on bankruptcy, we find other evidence that the disaster loans help firms fulfill their obligations: disaster loans reduce the share of firm debt that is delinquent and the duration of delinquent debt. These effects mostly represent staving off adverse outcomes that occur at declined firms.

Beyond the recipient (or "focal" firm), we are interested in the effects of disaster loans on businesses in the local community. On one hand, neighbors may benefit if foot traffic increases and the focal firms serve as amenities. For example, a nail salon at a strip mall may benefit from the presence of a grocery store, suffering if the grocery store fails. On the other hand, the SBA loans may serve a certification function or lead to snowballing of benefits, crowding out activity at other firms. Using Census data on firms in the focal firm's Census tract, we find that receiving a loan increases local firm entry by about eight firms, or 8% of the mean. However, when it comes to incumbent neighbors of the focal firm, which we define as retail businesses in very close proximity to the focal firm, we see no evidence of positive spillovers. If anything, there is a negative impact, and the results for adverse financial outcomes are consistent with crowding out. These results point to a positive externality on the entry margin (i.e., for new firms into the neighborhood), but a possible negative externality from SBA loans for pre-existing firms. However, it is possible that the negative externality reflects the non-applicant neighbors of declined firms doing better than the damaged focal firm that fails to obtain an SBA loan. While we cannot speak to welfare effects, these results relate to the process of creative destruction that is accelerated by a disaster. As new entrants—especially those that are employer firms—are disproportionately responsible for productivity and employment growth (Haltiwanger, 2009; Decker et al., 2014), it seems likely that the overall spillovers are positive.

This paper sheds light on the effect of access to credit during periods of distress. In private markets, credit is priced according to risk, so comparing effects of loans on borrowers with different characteristics is difficult, as they are paying different prices. In our context, all borrowers during the same disaster receive the same interest rate and, roughly, the same loan terms. This allows us to compare the effect of a loan across different groups. We find that for older firms, the strongest effect of the loans is to prevent exit, while the effects on firm growth are concentrated in younger firms. This latter result is consistent with government aid policies being more effective for younger firms because they are more financially constrained (Howell, 2017) and perhaps because they have more interest and opportunities to expand and adapt to the post-disaster environment. We also observe larger negative effects on both real and financial outcomes in neighborhoods with above-median Black populations, and a much larger mitigation of exit in neighborhoods that were struggling economically after the disaster. In sum, it appears that the SBA loans are more useful for firms and places that are more constrained and have more vulnerable populations, suggesting that SBA loans alleviate severe credit market frictions in these areas following disasters.

Our results have important implications for policy. Since SBA disaster loans are provided directly to businesses with no intermediation fees and have low loss ratios, with interest income covering defaults on average during our sample period, they are a relatively low-cost policy.[4] This contrasts with other disaster relief policy options, such as direct transfers to affected citizens, grants or forgiveable loans to firms, and more generally paying for intermediation.[5] By combining the real outcomes from administrative tax data above with financial data from a major credit bureau, we shed light on how a government loan affects both the firm's real and financial sides. It is rare to observe both sides simultaneously, especially outside of publicly traded firms. Our findings suggest that disaster loans are a useful and cost-effective tool, supporting both recipient businesses and enabling entry.

This paper contributes to three strands of literature. The first studies government lending programs. A

[4]For example, see here and here.

[5]For example, in the COVID-19 Paycheck Protection Program, the SBA incentivized private lenders to process the forgiveable loans with a fee that averaged 3% of the loan amount, corresponding to roughly $24 billion in fees (Benoit and Rudegeair, 2020).

key challenge in this research is finding identifying variation to conduct causal assessments. For example, existing research on SBA loans, such as Brown and Earle (2017), has relied on matching strategies with non-applicant firms. One advantage of our setting is that we can use application data to identify causal effects; these data are unavailable for other SBA programs that are privately intermediated. The literature on government loans and loan guarantees during normal times includes Lelarge, Sraer, and Thesmar (2010), Banerjee and Duflo (2014), Brown and Earle (2017), Mullins and Toro (2017),Barrot et al. (2019) and Bachas et al. (2021). Small business disaster loans have received little attention, with analyses to our knowledge restricted to survey or county-level data.[6] There is also work on the impacts of forgiveable SBA loans and grants during the COVID-19 pandemic (Humphries et al., 2020; Balyuk et al., 2020; Howell et al., 2022; Granja et al., 2022). Broadly, a theme of this literature is that indirect government lending programs administered through private lenders face severe targeting challenges (also see Agarwal et al. (2017, 2018)).

Second, we contribute to the literature on the consequences of credit frictions (Petersen and Rajan, 1994; Berger and Black, 2011; Midrigan and Xu, 2014; Darmouni, 2020). A subset of this work focuses on how financing frictions affect entrepreneurship and growth (Nanda and Rhodes-Kropf, 2016; Schmalz et al., 2017; Howell, 2020). This paper instead examines the importance of liquidity during unexpected negative shocks. While disasters are external, observable, and exogenously timed, the dire consequences for businesses that did not receive disaster loans in our setting suggests important frictions leading otherwise profitable businesses to fail. By linking data from a government lending program, business credit reports, and administrative data on outcomes such as survival and employment, we connect the financial and real economic consequences of frictions that prevent firms from improving their physical capital.

Finally, a growing literature examines how markets and governments manage severe climate risks (e.g., Baez et al., 2017; Baldauf et al., 2020; Deryugina and Molitor, 2018; Engle et al., 2020; Gallagher et al., 2023). One related strand studies government programs and the incentives that they create, especially the National Flood Insurance Program (Collier and Ragin, 2020; Kousky and Michel-Kerjan, 2017; Mulder, 2021; Sastry, 2022). Several papers examine disaster recovery lending to households, showing that underwriting standards may limit access to recovery loans for credit constrained households and that consumers are sensitive to loan terms such as interest rates and collateral requirements (Billings et al., 2022; Begley et al., 2020; Collier et al., 2021; Collier and Ellis, 2022). There is also work on how disasters affect businesses and the local economy, which includes Leiter et al. (2009),Hornbeck (2012), Felbermayr and Gröschl (2014), Hornbeck and Naidu (2014), Gallagher (2014), and Miao and Popp (2014). Our study is the first causal assessment of the effects of disaster loans on businesses and their neighbors. Our results indicate an important role for government intervention in business credit markets that benefit not only affected firms but also the local economy.

[6]This includes Dietch and Corey (2011), Haynes et al. (2011), Marshall et al. (2015), Josephson and Marshall (2016), Davlasheridze and Geylani (2017), and Hiramatsu and Marshall (2017).

2 Institutional Context and Summary Statistics

2.1 Institutional Context

Background on SBA Disaster Loan Programs. Through its Office of Disaster Assistance (ODA), the SBA offers recovery loans following a declared disaster to businesses of all sizes, most private nonprofit organizations, homeowners, and renters. Between its inception in 1953 and 2019, the SBA provided approximately \$60 billion in disaster recovery loans as of 2019. (The program was greatly and temporarily expanded during the COVID-19 pandemic in 2020 to provide pandemic-related economic injury loans.) These recovery loans are the only U.S. form of federal disaster assistance provided directly to businesses, and unlike other SBA programs, they are underwritten, originated, and serviced by the SBA directly. We focus on these business loans exclusively in the following program description.[7]

The primary use of recovery loans is for businesses to repair or replace damaged property after a natural disaster.[8] Damaged property must be owned by the business and can include real estate, leasehold improvements, inventories, supplies, machinery and equipment. Almost all (94%) recovery loan applications are associated with a presidential disaster declaration. For these declarations, the Federal Emergency Management Agency (FEMA) coordinates the local response, establishing temporary offices in affected neighborhoods. Businesses harmed by the disaster are encouraged to register with these FEMA offices. These firms are then automatically contacted (via email, robocalls, and letters) by the loan program.

Figure 1 shows the dispersion of applicants across U.S. counties in our data, which cover 2005 to 2017. The shading reflects the log number of applicants in each county. Disaster loan applicants come from throughout the U.S., reflecting the geographic dispersion of natural disasters including storms, tornadoes, and wildfires. Applications are concentrated in areas prone to hurricanes, especially along the Gulf Coast.

Loan Eligibility and Terms. Businesses of any size are eligible to apply for a disaster loan.[9] Owners need not be a U.S. citizen, though they must have legal residency status. Disaster recovery loans are long-term, low-interest, secured loans. The maturity is typically around 15 years, with a maximum term of 30 years, and is based on the applicant's ability to repay. Interest rates are fixed for the duration of the loan, and averaged 3.78% during our sample period.

[7] For additional details, see ODA (2018).

[8] Most loans (93%) are accompanied by an additional Economic Injury (EI) loan to offset income losses. A small share, 5.7% of applicants have EI loans only. As we find no heterogeneous effects depending on whether a loan has an EI component, we do not address it further.

[9] Businesses can include most private non-profits, small agricultural cooperatives, small aquaculture businesses, and owners of commercial or residential rental property. Other agricultural businesses including nurseries, as well as lending, investment, or other speculative activity businesses, and real estate developers, are ineligible.

Most loans are secured with collateral, which is required for all loans above a certain amount (e.g., $25,000 as of 2018). However, the SBA will not decline a loan for lack of collateral. The preferred type of collateral is real estate, but the SBA will take other forms of collateral if no real estate is available. In addition to collateral, the SBA requires all principals to provide a personal guarantee (except for sole proprietorships), which is either secured or unsecured. When the loan is fully secured with real estate collateral, the guarantee may be unsecured. If the business has inadequate real estate equity to fully collateralize the loan, the guarantees must usually be secured.[10]

Loan Process and Underwriting The business must apply for a loan within nine months of the disaster declaration, either online or at an SBA field office. For cases in which a business has multiple owners, each owner must complete an application form as part of the business application. The application permits the SBA to verify property damage through an onsite loss inspection of the business and, for both the business and the owners, to collect income information from the IRS and credit bureau reports.

While disaster recovery loans are subsidized and the SBA does not seek to make a profit, the program emphasizes minimizing costs to the taxpayer.[11] It therefore screens applicants on creditworthiness primarily using two pieces of evidence. The first is the owners' credit scores, specifically their FICO scores. The SBA evaluates whether the highest credit score among the owners exceeds a threshold credit score, which varies over time. As we explain below, we build our identification strategy on the basis of the discontinuities in approval probability created by these FICO thresholds.[12] The second piece of evidence is an evaluation of business cash-flows prior to the disaster to assess whether the business will be able to service additional debt.[13]

For each disaster, the program offers only two interest rates: one for firms that are deemed unable to get credit elsewhere, which accounts for about 80% of loans, and one for firms that are deemed able to get credit elsewhere, which is higher and accounts for the remainder. For example for businesses affected by Hurricane Harvey, businesses who were deemed credit constrained borrowed at an interest rate of 3.305% vs. 6.61% for the remaining businesses.[14]

The SBA can only lend to repair damages that have not already been funded through insurance or other

[10]In some circumstances the SBA accepts limited guarantees and affiliate guarantees (when the cash flow of the affiliate is necessary for repayment).

[11]A loan officer and a supervisory loan officer together decide whether to approve the loan. The documentation is produced by the loan officer, and the supervisory loan officer must then review her work and come to the same conclusion. If they disagree, a higher level committee makes a determination.

[12]SBA also requires a credit bureau report for the business when the loan amount is above $200,000.

[13]The SBA's cash-flow measures are immaterial to our analyses, but are reported in ODA (2018).

[14]The credit elsewhere test assesses if the business meets two criteria: one related to monthly cash flows and the other to business equity. Businesses with more slack in their cash flows and less balance-sheet leverage are more likely to be deemed able to access credit elsewhere.

proceeds (e.g., through charitable donations). Thus, after calculating the cost to repair damages, the loan officer subtracts any proceeds to determine the eligible borrowing amount. The maximum possible loan size is $2 million.

Loans are disbursed in stages to ensure funds are spent according to the agreement, and based on actual physical repairs. The final aspect of the loan process is repayment. There is a standard deferment of the first payment for four months, though there are options to defer longer. After this deferment period, repayments consist of equal monthly installment payments of principal and interest, which fully amortize the loan amount and the interest accrued during the deferment period.

3 Estimation Approach

This section explains our estimation strategy. We first describe the discontinuities that form the basis for identification. Then we explain the instrumented difference-in-differences design.

Credit Score Discontinuities The owner's FICO score is a key metric in the underwriting process (ODA, 2018, p. 101). The SBA has employed target credit scores in underwriting and has varied these targets over time.[15] While the SBA does not explicitly state the target thresholds, we observe them in the data because the approval likelihood jumps discretely at certain credit score thresholds. For example, Panel (a) of Figure 2 shows the relationship between credit score and loan approval for disaster that occurred in 2017. In 2017, loan approval increases by 20 pp at a credit score of 570. Since the program varied the credit score thresholds used in loan underwriting over time, we have a set of natural experiments composed of credit score thresholds specific to the year in which a disaster occurred. Whether an applying business participates in the experiment depends on two sources of plausibly exogenous variation: the timing of the natural disaster and whether the owner's credit score is near a discontinuity.

To find the credit score discontinuities over time, we use an algorithm adapted from Argyle et al. (2020). We partition the data by years, assigning applicants to the year of their disaster declaration date. For each year, we regress the approval probability on bins of the owner's credit score (each bin includes 10 FICO points). We define a credit score discontinuity using three criteria. First, the change must be economically meaningful: the approval probability must change by at least 5 pp at credit score bin c relative to the previous credit score bin. Second, the change must be statistically significant (at the 5% level). Third, approval must be smooth near the threshold: the change in approval probability from the nearest adjacent credit score bins

[15] In our communications, managers reported that the program's underwriting experimentation related to balancing the program's goals of expanding post-disaster credit provision and minimizing costs to taxpayers by ensuring the repayment capacity of approved applicants. Its experiments related to varying over time target credit scores and the weighting assigned to credit scores relative to business cash-flows (the other key underwriting criterion).

(the bins just above and below bin c) must be statistically insignificant (at the 10% level).[16] The algorithm identifies 22 threshold-by-year discontinuities. We normalize applicants' FICO scores by subtracting the relevant threshold value and combining data from all 22 discontinuities. We include applicants within a bandwidth of 29 FICO points, which reduces overlap between possible discontinuities (the results are robust to alternative bandwidths). Panel (c) of Figure 2 shows the combined discontinuity. Businesses are 12 pp more likely to be approved if their owner's FICO is above the threshold.

The discontinuities range from FICO scores of 540 to 780 over the years 2005 to 2017. The 22 natural experiments represent 13 distinct FICO thresholds, 12 distinct years, and 916 distinct natural disasters.[17] By leveraging these natural experiments, we can examine the effects of loan approval for a population with a broad range of credit scores. This approach stands in contrast to many regression discontinuity designs (RDDs), which rely on a single threshold for identifying variation and can speak only to the treatment effects of individuals near that threshold. Panel (b) of Figure 2 shows the discontinuities; the vertical axis reports the change in approval probability at the threshold. Panel (d) shows the number of applicants for each discontinuity.

The Appendix A provides additional analyses regarding the discontinuity. We examine the threshold for continuity in firm characteristics, including the number of employees, firm age, and disaster-related loss amount, and find that each is smooth through the FICO threshold. We also conduct a McCrary test for evidence of manipulation at the threshold and do not find sorting above the threshold. We also provide regression estimates of how the threshold affects approval likelihood in models controlling for the running variable and fixed effects for ZIP code and disaster year by FICO threshold. Across specifications, firms just above the threshold are 10 to 15 pp more likely to be approved for a loan; in all cases, the threshold is a highly significant predictor of approval.

Estimating Equations. We leverage the credit score discontinuities to approximate the ideal experiment of randomly allocating loans to a subset of firms. Consider a naïve estimation in which we regress a firm outcome y_{it} on whether the firm was approved for a disaster recovery loan. We observe applying firms before and after the disaster so can estimate the difference-in-differences model

$$y_{it} = \beta Approved_i \times Post_t + \gamma_i + \delta_{tjc} + \varepsilon_{it} \tag{1}$$

for firm i and event time t. $Approved_i$ is an indicator for loan application approval, and $Post_t$ is an indicator for observations that occurred after the disaster. Each firm is associated with a single disaster, and γ_i is a

[16]These criteria represent a trade-off in that making them less stringent increases the sample size by including more discontinuities but also reduces the strength of the discontinuity as an instrument for approval. We find qualitatively consistent results when adjusting the stringency of the criteria.

[17]We find discontinuities in each year except 2013, which was a relatively mild year in terms of natural disasters.

firm fixed effect.

The model includes three additional fixed effects which we interact to construct δ_{tjc}. Each of the 22 natural experiments described above represents a disaster-declaration-year j by credit-score-threshold c combination. For example for applicants affected by disasters occurring in 2017, the program used a credit score threshold of 570. Each experiment gets its own event-time fixed effects (e_t), taking values such as -2 to represent the second year before the disaster year. Interacting fixed effects for event time, disaster declaration year (d_j), and credit score threshold (s_c) yields

$$\delta_{tjc} = e_t \times d_j \times s_c.$$

The experiment-specific time fixed effects help generate clean control-group estimates for each experiment. This stacked regression design addresses concerns that in a setting with staggered treatments, fixed effects that are shared across treatments can bias estimates of the average treatment effect (Baker et al., 2022; Cengiz et al., 2019).

Equation (1) does not offer a causal assessment because loan approval co-varies with firm characteristics. Instead, we use the credit score discontinuities as an instrument for approval. Specifically, we estimate the 2SLS model

$$\begin{aligned} Approved_i \times Post_t &= \lambda \mathbb{1}(FICO_i \geq 0) \times Post_t + \theta_i + \kappa_{tjc} + u_{it}. \\ y_{it} &= \beta \widehat{Approved_i \times} Post_t + \gamma_i + \delta_{tjc} + \varepsilon_{it} \end{aligned} \tag{2}$$

The second stage uses predicted approval $\widehat{Approved_i \times} Post_t$ in an instrumented difference-in-differences estimation. Thus, the first stage effectively randomizes treatment in the limit of the discontinuity, and the second stage leverages both pre- and post-disaster observations to estimate treatment effects. The first stage includes the same fixed effects as the second stage: firm fixed effects θ_i and event-time by disaster-year by credit-score-threshold fixed effects κ_{tjc}. Building on the continuity assumptions of the RDD, the instrument provides a LATE interpretation under the additional assumption that the instrument has the same directional effect on all applicants (i.e., the setting includes no defiers). This additional assumption seems likely to hold because the program documentation codifies basing loan approval on credit score (ODA, 2018). Also, approval likelihood jumps at the credit score threshold for each of the 22 identified discontinuities, not just on average across the experiments (Figure 2 Panel B).

We use several variations of this baseline model. First, we estimate an event study version of the baseline model, which adds event time indicators. These 2SLS models use a set of instruments, one for each of the k

approval-by-event-time interaction terms:

$$Approved_i \times \mathbb{1}(t=k) = \lambda \mathbb{1}(FICO_i \geq 0) \times \mathbb{1}(t=k) + \theta_i + \kappa_{tjc} + u_{it} \tag{3}$$
$$y_{it} = \sum_{k=-5, k\neq -1}^{7} \beta_k \widehat{Approved_i \times \mathbb{1}}(t=k) + \gamma_i + \delta_{tjc} + \varepsilon_{it}$$

That is we examine loan approval on firm outcomes starting 5 years before and ending 7 years after the disaster, using the year before the disaster $t-1$ as the reference period. Each event-time period k receives its own first-stage equation (modeling $Approved_i \times \mathbb{1}(t=k)$), except for the reference period.[18] An additional benefit of this event study model is that it allows for examination of pre-trends. While we expect the RDD design to randomize treatment, pre-event observations facilitate an assessment of parallel trends before the disaster.

To assess spillovers, we apply the baseline model to consider the effect the approving firm i on neighboring, non-applicant firm m. Specifically, we estimate the 2SLS model

$$Approved_i \times Post_t = \lambda \mathbb{1}(FICO_i \geq 0) \times Post_t + \theta_m + \kappa_{tjc} + u_{mt} \tag{4}$$
$$y_{mt} = \beta \widehat{Approved_i \times} Post_t + \gamma_m + \delta_{tjc} + \varepsilon_{mt}$$

Finally, as an alternative specification for robustness, we replace firm fixed effects with ZIP fixed effects in the baseline model. Those models include quadratic controls for the running variable $f(FICO_i)$ and an additional first stage equation (instrumenting for $Approved_i$ with $\mathbb{1}(FICO_i \geq 0)$). Our baseline model omits these terms as they are collinear with firm fixed effects.

4 Data and Summary Statistics

We use three main datasets in analysis. The first is application and loan approval information for all disaster loan applications between 2004 and 2019. The second is U.S. Census Bureau panel data on firm characteristics and real outcomes. The third is Experian credit bureau panel data on firm financial characteristics.

[18]For the reference period, we would normally incorporate an additional first-stage modelling the direct effect of being approved $Approved_i$ (without event-time interactions); however, approval is determined once for each applicant, making it time-invariant. Thus, $Approved_i$ is collinear with firm fixed effects and that first stage cannot be estimated. As we note below, we also examine versions of this model that replace firm fixed effects with ZIP fixed effects in robustness tests; in those, we incorporate the additional first stage for $Approved_i$ as well as quadratic controls for FICO score (the running variable).

Loan Application Data. Our SBA disaster loan application data include 167,202 unique business applications.[19] Table 1 provides aggregate statistics. The data include 54,532 unique borrowers, which collectively have 236,571 employees. We observe more than $5.3 billion in disbursed loans. The rate of approval conditional on application is about 44%. The rate of borrowing conditional on application is 33%, because some approved firms never take up a loan.

Hurricanes account for 73% of disasters. The next largest category is storm or flood, at 14%. We have small numbers of applications following tornadoes, wildfires, oil spills, and droughts. Over half of applicants were sole proprietorships and a quarter were corporations. The most represented industries are real estate (includes landlords who rent or lease their property), miscellaneous services (such as hair salons, retail trade, accommodation and food services, professional services, and construction), and retail.[20]

We present summary statistics for continuous variables in Table 2. The median firm is eight years old and has just one employee. The distribution is, as expected, skewed right for both variables, with the averages being 13 years and 4.6 employees. The average and median amount lost by applicants, as assessed by SBA's loss verification protocol, are $156,442 and $46,772. In the bottom panel, we present variables describing the loans disbursed, all of which are skewed left. The average (median) loan amount is $72,667 ($18,389). The average (median) interest rate is 3.8 (4.0), and the average (median) term of the loan is 18.9 (16.8) years, and the average (median) monthly payment is $685 ($274).

U.S. Census Bureau Data. The application data are matched to the U.S. Census Bureau's Business Register, which contains all business establishments in the U.S. private non-farm sector with at least one employee. Matching was conducted by U.S. Census Bureau staff.[21] They successfully matched 82% percent of the SBA applicant firms. We employ outcome data from two Census Bureau sources. The first is the Longitudinal Business Database (LBD), which begins in 1976 and ends in 2019. The LBD is the universe of non-farm, non-public administration business establishments with paid employees. The second is the Integrated LBD (ILBD), which also includes nonemployer firms.

Summary statistics about the analysis sample (i.e., within the RDD bandwidth) are in Table B1. These include 24,000 unique firms. We employ four firm-year outcome variables from the LBD. The first outcome is exit, which is observed when a firm is not found in the ILBD or LBD for the rest of our sample period. In a given year, 12% of firms exit. The second is deformalization, when a firm transitions from an employer to a non-employer. We construct this by pasting together firm-years that appear in the LBD with those that

[19] These data are proprietary to the SBA and are non-public. They are employed here via special contracts between the researchers, the U.S. Census Bureau, and the SBA.

[20] Among all applications, NAICS codes are missing for 21%. The table reports percents among non-missing NAICS codes.

[21] They used a combination of the Social Security Numbers of applicant individuals (i.e., firm owners) and the firm EIN, when available. When not available, they used probabilistic and then clerical matching using firm names, addresses, and ZIP codes.

subsequently appear in the ILBD. The mean is 6%.

The third outcome is employment, which is observed quarterly after 2004 (before 2004, it is observed once per year, in the pay period that includes March 12). On average, firms have about three employees, though this includes many zeros for the nonemployers; the average is just over five among employer firms. These figures are smaller than the SBA application figures, likely because they include all firm-years, including many years pre-application when larger firms were younger and smaller. Also, note that the employment sample is smaller because nonemployers are not included; the share of nonemployers in our data is similar to the overall share of nonemployers among U.S. firms.[22] Finally, we use revenue, which is observed annually starting in 1996, but is only available for a subset of firms. Nonemployer firms do report sales as receipts, which we incorporate into this measure. The average is $351,000. To correspond with our other data sources, we construct annual measures for employment and revenue.

Credit Bureau Data. To understand the financial implications of disaster loans, we acquire data from Experian on firm credit histories. Credit reports represent a snapshot of the firm; our records were drawn on June 30 of each year. Lenders report to Experian on firms' credit balances and repayment behavior (e.g., the duration of credit delinquencies). Additionally, lessors and utilities providers report firms' repayment behavior on their contracts. Experian also collects bankruptcy filings through county records. The SBA disaster loan program does not report to Experian. The one exception is loan charge-offs: the federal government reports non-performing loans to Experian during the collections process.[23]

Table 4 provides summary statistics of the outcome variables used in the analysis. "Outstanding debt" is reported in thousands of dollars and is the firm's total credit balances. The average applying firm has around $8,000 in outstanding debt. Because of the SBA reporting process, only charged-off SBA disaster loans would contribute to this debt balance. The second row reports "outstanding debt, paid on-time" which is the total balance on the firm's debt that is paid in accordance with the agreed contract terms. Thus, this balance excludes any delinquent loans (including any charged-off SBA disaster loans). "Number of contracts" is a count of the new time-sensitive financial obligations that the firm has to lenders, lessors, telecom providers, and others. While the debt balance measures described above are specific to credit contracts, "number of contracts" comprises a broader set of commitments. "Delinquent share of debt" describes the share of total outstanding debt that is held in loans that are at least 90 days delinquent. While Experian also reports shorter-term delinquencies, this severe measure reflects firms' financial distress and likely has longer term implications for the firm's ability to borrow. Additionally, any charged-off SBA disaster loans should be

[22] This is about 75% over the course of our data. This is See e.g. Census Nonemployer Statistics.

[23] Specifically, the SBA transfers non-performing loans to the Department of Treasury, which pursues collection of the remaining loan balance and reports the delinquent debt to the credit bureaus, in accordance with the Debt Collection Improvement Act of 1996 (SBA, 2015; U.S. Congress, 1996). Managers at both the SBA and Experian confirm that SBA disaster loans are not reported to Experian except in this case.

reflected in these severe delinquencies. "Days Late on all Contracts" is a weighted average of the duration of a firm's delinquent debt. It is calculated on a +30 day basis; the mean of 16.7 indicates that on average, firms pay 46.7 days after being invoiced for payment.[24] "Bankruptcy" reports whether the firm files for bankruptcy in the current year.

Finally, to assess spillovers we make use of data on non-applicant firms from both the Census LBD and from Dunn & Bradstreet. For each focal firm, which is an applicant for a SBA disaster loan, we examine how the receipt of a disaster loan affects entry of new firms nearby and how it affects local, incumbent neighbor firms. We provide more details regarding how we identify firm entry and incumbent neighbor firms when we examine spillovers in Section 6.

5 Results

Real Outcomes We first examine the effects of receiving a disaster loan on firm real outcomes, both on the extensive and intensive margins. We expect that whether a firm can repair physical capital destroyed in a disaster in a timely fashion may be central to its survival and success. In turn community recovery may be tied to the fortunes of local firms. However, the SBA loans are not unambiguously good either for the firm or for the community. First, they represent additional interest-bearing debt, which increases firm risk and thus the chances of firm failure. Second, we might think some firms should exit in a process of creative destruction. If the loans keep such "zombie" firms alive, they may not be useful for the community.

To explore these possibilities, we consider four outcomes in Panel A of Table 6 using the causal IV estimation strategy from Equation 2. The table includes the Kleibergen-Paap first-stage F-statistic, measuring the strength of the instrument for each estimation. Total observations are rounded to the nearest thousand due to Census privacy restrictions. The table also reports the mean of the outcome variable for each regression to facilitate interpretation of the estimated LATE.

First, we are interested in firm failure (exit) in column 1. Exit is clearly an undesirable outcome for the firm itself and is also likely to have negative effects on the community, subject to the creative destruction caveat mentioned above. Exit is a binary variable, capturing permanent closures. Receiving a loan reduces the chances of exit by 13 percentage points, which is 115% of the mean. This very large effect implies that the loans enable firms to survive that otherwise would not. A related outcome is transitioning from an employer firm to a nonemployer firm, which implies lower chances of growth and lower benefits for the community through employing workers. This declines by 5 percentage points, or about 85% of the mean,

[24]The delinquency measure is used by the lending industry and called "Days Beyond Terms."

though it is noisy. The sample size is smaller in column 2 relative to column 1 because it is restricted to ever-employer firms, which means that at any point over our sample period, the firm had employees. (Note that when a firm deformalizes, it is no longer an employer, so variation in column 2 is identified off of firms that were employers at some point before the disaster).

The dynamic effects representing estimates from Equation 3 for these two outcomes are in Figure 3 Panels A-B. The disaster occurs sometime during year zero. In general, we therefore anticipate that for some outcomes we might see effects in year zero, driven by disasters that occurred relatively early in the year. However, since many disasters occur later in the year (especially during hurricane season in late summer), any results are likely to be partial or noisier than in subsequent years. Note that since the firms are by construction alive (or ever employers) before the disaster, we cannot estimate pre-event coefficients for exit and deformalization. Therefore, these plots are informative about the dynamics of effects but do not serve as normal event studies, where we can assess pretrends.

The effect on firm exit grows over time (Panel A). Exit is a binary variable that switches from 0 to 1 in the year that the firm exits and remains 1 thereafter. Thus, the treatment effect measures the the effect of the loan on the likelihood of exiting by a certain year. Approved firms are around 20 pp less likely to have exited seven years after the disaster. This patterns points to a divergence, where the recovery loan helps businesses avoid persistent consequences of the disaster that the denied firms experience. Moreover, this pattern does not align with the notion that these loans are delaying exit of "zombie" firms.[25]

The third outcome, employment, speaks to the health of the firm and is likely especially relevant to broader local economic recovery. We use the log of one plus employment, so that the dependent variable is zero for firms that do not have employees, including those that exit. In column 3 of Table 6, we find that employment increases by 18%, which implies about half a worker at the sample mean. (Here and subsequently, we exponentiate coefficients for logged outcome variables to interpret the results relative to the mean.) We use the same sample of ever-employers as in column 2. The coefficient on revenue, in column 4, is large and positive but insignificant. Recall that the sample is smaller for revenue because of data limitations in the LBD; revenue is missing for many firms.[26] Figure 3 Panels C-D contain the event studies for these outcomes. Employment increases significantly starting in the year after the disaster year and remains elevated for at least five years.

Employer firms are more important for growth than nonemployers, even though they are the minority

[25] If disaster loans were primarily supporting zombie firms, we would expect that the loan would reduce exit in the year of the event; however, as loan payments become due, the exit rate for zombie firms would rebound and even turn positive in the following years.

[26] This is because revenue comes from tax forms that do not always merge with the core databases behind the Business Register, in part because it is only reported at the firm rather than establishment level, and sometimes under a different EIN than the employment and payroll data. Revenue is more often missing for nonemployers and in the initial years after firm entry.

among firms in the overall economy (Haltiwanger, 2022). In Panel B of Table 6, we restrict the sample to firms that were employers in the year before the disaster. Here, we find much larger and more robust results, most strikingly for employment and revenue, where employer firms tend to have higher and likely more accurately measured information. Here, an SBA loan reduces the chances of exit by 17 percentage points, which is twice the mean. Unsurprisingly given the sample restriction, the effect on deformalization become more robust (only firms with employees can deformalize), at 12 percentage points, which is also about twice the mean. Employment increases by about 45%, which in this subsample represents 2.25 workers. Finally, revenue increases significantly in this sample, by about 200% of the mean. Across Figures 3 and 4, there is no evidence of pretrends, consistent with a valid IV-RDD. The event studies also shed light on dynamics; they show that the effects persist for at least five years, and indeed grow stronger over the first five years before appearing to level out.

In sum, receiving a disaster loan has strong and persistent positive effects on real firm outcomes, especially for employer firms. They not only stave off bad outcomes—firm exit and deformalization—but also increase good outcomes—employment and revenue. These effects have positive implications for the local economy and tax revenues.

Private Credit Do SBA disaster loans unlock additional private credit, or do they substitute for it? By combining the real outcomes from administrative tax data above with financial data from a major credit bureau, we are able to shed light on the interaction between the firm's real and financial sides. It is rare to observe both sides simultaneously, especially outside of publicly traded firms. Here, we first consider the "bright side" of the financial variables, which is non-SBA private credit and regular contractual obligations, such as leases.

How SBA disaster loans affect private credit balances is unclear. SBA disaster loans and private credit may be substitutes. If so, then absent SBA loans, firms would have turned to private credit markets to repair their physical capital. In this case, SBA disaster loans would reduce private credit balances. This would mean that the program is crowding out private capital and may be a poor use of taxpayer resources. Alternatively, disaster loans may complement private credit. The SBA disaster loan might make firms attractive to private lenders for several reasons: e.g., repairing physical capital makes the firm more productive, it restores collateral values, or it acts as a certification (i.e. signaling) mechanism. In this case, the SBA disaster loan would increase private debt balances.

We consider three outcomes in Table 7 Panel A. (Recall from Section 4 that these variables are drawn from a snapshot, the firm's position in Experian on June 30 of the given year.) An SBA loan dramatically increases non-SBA private credit, with overall outstanding balances rising by nearly $18,000 (column 1), and outstanding balances that are reported as active in the most recent 30 days rising by $9,000 (column

2). In both cases, these effects represent a bit more than a doubling of the sample mean. Last, the number of contracts, which is a holistic measure of the firm's time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others, rises by 0.6, which is 116% of the mean. The event study coefficients are plotted in Figure 6. We see no evidence of pretrends, again consistent with a valid quasi-experimental design, and then a discontinuous increase after the disaster. The effect is persistent for at least seven years after the disaster year.

To interpret these large effects, it is helpful to compare the dynamics of raw mean balances across accepted and rejected loan applicants. In Appendix Figure C2, we present a series of plots for each financial outcome showing the average values of the outcomes separately for approved and rejected applicants, centered around the disaster year as in the dynamic IV RDD plots. Note that the the IV result is identifying off of compliers with the FICO threshold discontinuities and includes a rich set of controls, so it is possible that we might expect quite a different pattern in raw means. In practice, we see that the divergences in raw means after the disaster are in the same direction as the IV results albeit with different magnitudes. For example, Panel A shows that continuous balances track closely across the two groups until the first and second years after the disaster, when the approved group raises much more private debt while the rejected group raises somewhat less. The graph suggests that the effect on balances emerges from unlocking additional private debt for approved firms, rather than mitigating a big falloff in balances for rejected firms.

It is possible that the estimated differences in private credit result mechanically from the effects of SBA loans on survival: while surviving firms may continue to take on debt, exited firms cannot. We test whether the credit effects reflect survival. Panel B of Table 7 uses the Experian sample matched to Census Bureau data, where we can observe survival, and restricts the sample to firms that survived at least until the end of the Census data sample, which is 2019. The results are quite consistent with Panel A, indicating that the additional credit is not closely tied to survival. Instead, overall these results indicate that the SBA loans also help the firms attract additional investment from the private sector and maintain activity with vendors, consistent with a positive outlook for firm growth.

Adverse Financial Outcomes Receiving an SBA disaster loan increases the firm's debt burden, at a time when it is trying to recover from a disaster and its prospects are highly uncertain. More leverage should mechanically increase insolvency risks. Therefore, if the firm is not on a path to growth—for example, if the loans often go to firms that would efficiently exit post-disaster—or is already on the cusp of failing to meet pre-existing obligations, the SBA loan is likely to increase delinquency and ultimately bankruptcy. Alternatively, the SBA loan, which is specifically designated for rebuilding, may enable a firm to recover its productivity, allowing it to service its existing debt while also taking on the new financial commitments imposed by the disaster loan. This ability to meet existing obligations may help explain why disaster loan recipients are so much less likely to exit.

Using the Experian-matched sample, we examine three adverse financial outcomes in Table 8. First, we find that receiving a loan reduces the share of debt that is reported delinquent dramatically, by 34 pp, which is more than twice the mean (column 1). Second, we find that a loan reduces the number of days that the firm is late in paying on all contracts—which includes leases, utilities, and other regular obligations—by 35 days (200% mean, column 2). To interpret these large magnitudes, it is useful to consider as above how the conditional raw means change for accepted and rejected loan applicants. Appendix Figure C3 Panels A and B show that after the disaster, both approved and rejected applicants experience large increases in the share of debt delinquent and days late, consistent with a large negative shock to the firm and the local economy. However, the increases are much larger among the rejected group; for example, the delinquent share roughly triples for the declined applicants and doubles for the approved applicants. This dramatic widening helps to explain the large effect.

Figure 6 Panel A and B show that in the dynamic IV model (Equation 3), there is no evidence of a pre-trend in the years before the disaster for either share delinquent or days late. Both subsequently decline before stabilizing in the fourth year after the disaster year. This contrasts with the outstanding balances and contracts dynamics from Figure 6 Panels A and C, where the positive outcomes stabilize by the second year after the disaster. Therefore, it does not seem that changes in total balances can explain the continued fall in the share delinquent. This suggests that the decline in delinquencies is not due to paying off old debt with new debt or to a larger denominator of balances in the share delinquent.

The third outcome is bankruptcy, which is one type of exit that is a key outcome for our study. This is because the real outcome of exit (examined above) is not necessarily a bad thing from a social perspective; indeed, it might be desirable if the firm is unproductive. In contrast, much evidence suggests bankruptcy is costly, including the transaction costs of filing and proceedings and negative effects on lenders (Bernstein et al., 2019; Dou et al., 2021; Antill, 2022). Column 3 of Table indicates that a loan reduces the chance of bankruptcy by 3.8 pp, which is more than 100% of the mean. Note that consistent with having experienced a large negative shock, the overall rate of bankruptcy in our sample is quite high relative to the population of small businesses, at more than 20 times the national rate.[27]

We restrict the sample to ever-survivors in the Census-matched sample in Panel B of Table 8. Unlike in the case of private credit from Panel B of Table 7, the effects on all three adverse outcomes become insignificant in this sample. The coefficient on delinquencies is still reasonably large in magnitude, but the effects on days late and bankruptcies become much smaller, with the bankruptcy coefficient is close to zero. This implies that at least bankruptcy and days late in repaying debt are precursors to exit, helping to explain

[27]In 2017, there were 23,100 business filings (amazingly, in 2021 only 16,140). There are about 32 million small businesses. So that's an overall rate of 0.00072, while in our sample it's 0.017, a 23x increase. See here and here.

that real effect. This connection between the real and financial side of the firm suggests that an important channel for explaining the effect on firm exit: absent a disaster loan, firms are unable to recover sufficiently to fulfill their financial obligations.

We can continue to connect the financial and real outcomes by exploring how firm exit is related to adverse credit events, and whether this differs across firm type. This can help shed light on the social costs of the exit effect. In Table 9, we use the Experian-Census matched sample to separate the exit events into those that occur in firms with delinquencies, bankruptcy, and neither of these (all other).[28] In the full sample, exit is dominated by the "other" category (Panel A), which we expect given the large share of nonemployers, which are unlikely to file for bankruptcy. This “other” exit describes firms without debt closing or firms paying off all of their debts and then closing. However, when we restrict to employer firms in Panel B, we see that the decline in exit with bankruptcy is by far strongest effect relative to the mean (column 2). The effect on other types of exit becomes insignificant. Consistent with the results from Table 8 Panel B, reported delinquences do not seem relevant for exit. Overall, this table suggests that among employer firms, the SBA disaster loans play an important role in deterring exit via bankruptcy in particular.

OLS Results For the main real and financial outcomes, we report OLS results in Appendix Table C1, and event studies in Appendix Figures C1, C5, and C4. While the OLS results do not have a causal interpretation, they provide a useful reference by comparing outcomes for approved versus declined firms. Overall, the OLS results are consistent with the IV results in being uniformly in the same direction and highly statistically significant. For example, the IV LATE for private debt is about $17,700, while the OLS estimate is $11,900.

As in this case of private debt balances, the estimated effects are in general larger for IV than OLS. The larger IV effect indicates that the impact among compliers with the RDD threshold design—that is, within the narrow bandwidth, the difference between firms with a FICO score above the threshold who are approved and those below the threshold who are declined—is larger than the average difference between all approved and declined firms. This difference can occur event if the exclusion restriction is satisfied (Angrist and Imbens, 1995; Jiang, 2015). A likely explanation in our setting is that loan officer discretion may introduce endogeneity, biasing the OLS results downward. Specifically, while the amount of physical damages that a business sustains is not an underwriting criterion, loan officers are given some discretion and may use this discretion to direct credit toward more damaged firms as those firms may have an especially great need. Consistent with this explanation, we see in Table 2 that approved firms have larger damages than declined ones. Larger damages are presumably harder to overcome so directing loans toward heavily damaged firms could explain attenuation of the effects in the OLS results. In contrast, the IV results reflect

[28]We identify a firm as having a bankruptcy or delinquency with exit if the financial outcome is positive in at least one of the two years comprising exit and the preceding year.

an effectively random assignment of loan approval and so would seem to more accurately capture causal effects.

6 Spillover Effects

We are interested in the effects of disaster loans on businesses in the local community. Above we showed that a disaster loan increases the recipient's chances of survival, growth, and access to private credit. Here, we examine how this impacts neighbors of that "focal" recipient firm. On the one hand, neighbors may benefit if foot traffic increases and the focal firms serve as amenities. For example, at a strip mall a nail salon may benefit from the presence of a grocery store, and may suffer if the grocery store fails.

On the other hand, the SBA loans may serve a certification function or lead to snowballing of benefits, crowding out activity at other firms. This could occur if the focal firm draws more traffic from its competitors because it is able to make repairs more quickly and effectively. Also, private creditors face information asymmetry, especially in lending to small businesses (Berger and Udell, 1995), and may treat the SBA loan as a signal of quality. The SBA loan might improve the firm's prospects, making it a better credit risk. Especially if private creditors are rationing capital, these forces could lead them to reallocate funds away from the neighbors and towards the focal firm.

To identify neighbor firms, we use the complete Census Business Register for analysis with the Census sample, and Dunn & Bradstreet for analysis in the Experian sample. We construct two measures: one of local entry and one of local incumbent neighbor firms. Both begin by identifying all other firms that did not apply for an SBA loan in the focal firm's Census tract. Entry is measured as the difference between the number of firms in the tract in year t and year $t-1$.[29] To construct the incumbent neighbors dataset, we then identify those firms in the focal firm's ZIP code that are also in the retail industry, since we expect that retail will be most sensitive to changes in traffic and neighborhood amenities.[30] Among this group, we retain the five nearest neighbors using an algorithm with the following preference step structure. First, the algorithm identifies best matches that are in the same census block. Second-best matches are on the same street and in the same tract. Finally, third-best matches are on the same street.[31]

To assess financial spillovers, we develop a set of incumbent neighbors for the focal firms using Dunn & Bradstreet (D&B) and then acquire Experian credit bureau panel data for them. This allows us to make use of the full Experian sample rather than only the subset matched to Census. Note that it is impossible to

[29] We truncate this variable at 100 entrants, there are some outlier tracts with many more entrants.

[30] Retail includes the following three-digit NAICS groups: 442, 443, 444, 445, 447, 448, 451, 452, 453 and 722.

[31] The algorithm stops when it reaches five firms at any given step. If there are more than five firms that are matched in a step then we randomly choose five. If there is no match for three measures, then we take a random sample of five from the zip code. To match over street, we clean street names and then use a string distance measure.

assess financial outcomes of the Census neighbors, because data on individual businesses (which Experian would require to match) cannot be taken out of Census due to disclosure restrictions. Therefore, we draw a set of neighbors from the complete D&B database from 2000 to 2019. We first geolocate each focal and D&B firm in ArcGIS, and then calculate shortest driving distance using an Open Source Routing Machine (OSRM).[32] As within Census, we then identified the closest five firms in the retail industries.

The results are in Panel A of Table 10. First, we consider firm entry into the neighborhood. We focus on the sample of focal firms with at least three employees, which could plausibly affect local amenities and neighborhood quality. The result, in column 1, indicates that receiving a loan increases local firm entry by about eight firms, or 8% of the mean.[33] (We find results in a similar direction using all focal firms, but it is not significant.) The next columns look at the four real outcomes for neighbors of the focal firm as of the disaster (i.e., incumbents). Here, we see no evidence of positive spillovers. If anything, there is a negative impact, as the coefficients on employment and revenue are negative; in particular, there is about a -20% effect on revenue.

The results form Panel A suggest possible crowding out of incumbent neighbors. One possibility, as suggested above, is that the focal firm's benefit from the SBA loan keeps the neighborhood appealing for new firms, but draws capital "allocated" to the area away from other incumbent firms, suggesting banks are to some degree rationing capital to disaster-affected firms. To assess this mechanism, we assess the financial impacts on D&B neighbors in Panel B of Table 10. We do not find precise effects, but the coefficients on adverse financial outcomes—delinquency, days late on contract, and bankruptcy—are all positive, consistent with crowding out (columns 1-3). Moreover, these positive coefficients are similar in magnitude to the negative coefficients for focal firms from Table 8. There is also a negative coefficient on number of contracts (column 6), which is also consistent with crowding out. More ambiguously, the coefficients on private non-SBA debt (column 4-5) are also positive. However, note that their magnitude is small; they are less than one third the positive magnitudes for focal firms from Table 7.

Overall, these results suggest that there is a positive externality on the entry margin, that is, a positive effect on new firms into the neighborhood, but that there also may be a negative externality from SBA loans for pre-existing firms. However, it is possible that the negative externality reflects the non-applicant neighbors of declined firms doing better than the damaged focal firm that fails to obtain an SBA loan. While we cannot speak to welfare effects, this relates to the process of creative destruction that is accelerated by a disaster. As new entrants—especially those that are employer firms—are disproportionately responsible for productivity and employment growth (Haltiwanger, 2009; Decker et al., 2014), it seems likely that the overall spillovers are positive.

[32]We geolocate using an existing address book available through NYU. OSRM is available here.

[33]The result is similar using the log outcome as well and not truncating the entry variable at 100 firms.

7 Variation in Benefit

An advantage of the setting is it sheds light on the effect of access to credit during periods of distress. In private markets, credit is priced according to risk, so comparing effects of loans on borrowers with different characteristics is difficult, as they are paying different prices. In our context, all borrowers during the same disaster receive the same interest rate and, roughly, the same loan terms. This allows us to compare the effect of a loan across different groups. We are especially interested in variation in proxies for vulnerability and more severe financial constraints.

First, we consider heterogeneity by firm age in Table 11. We expect younger firms to be more constrained because there is less information about them and they have fewer internal resources or assets to serve as collateral (Cabral and Mata 2003; Angelini and Generale 2008; and Hall 2008). They also tend to be more dynamic, as they are a key source of productivity and job growth overall in the economy (Decker et al., 2014). We split at the median age, which is seven years. For the Census outcomes, in Panel A, we report the results in the older firm sample for exit and deformalization, and the results in the younger firm sample for employment and revenue in order to capture the economically relevant findings. Relative to the main results in Panel A of Table 6, the effects among older firms on exit and deformalization are larger (columns 1-2), at 19% and 8% relative to 14% and 5%, respectively. When it comes to employment and revenue, we see a more dramatic difference; here the main effects are driven by younger firms (columns 3-4). Specifically, the effects on employment and revenue among younger firms are 28% and 87% relative to 18% and an insignificant 21% in the main sample, respectively. The effects are small and insignificant for older firms (unreported).

The financial effects for younger and older firms are in Panels B and C. We see meaningful effects in both groups, which is somewhat different from the real outcomes, but find generally larger effects relative to the sample mean among younger firms. This is especially true for the adverse effects (columns 1-3), but it is also true for the effects on private debt and number of contracts, which are larger among older firms (columns 4-6). For example, the negative effect on the days late in payment is 250% of the mean for younger firms (Panel B column 2), while it is only 130% of the mean for older firms (Panel C column 2). This compares with an effect in the full sample of about 200% (Table 8 Panel A column 2). These results are consistent with greater financial constraints among younger firms.

In sum, we find that for older firms, the strongest effect of the loans is to prevent exit, while the effects on firm growth are concentrated in younger firms. This latter result is consistent with government aid policies being more effective for younger firms because they are more financially constrained (Howell, 2017) and perhaps because they have more interest and opportunities to expand and adapt to the post-disaster environment.

Next, we explore variation at the neighborhood level. We examine neighborhoods with above-median Black populations, which is a proxy for being more vulnerable, poorer, and relatively more underserved by conventional private financial institutions. Specifically, we employ an indicator for the ZIP code having an above-median share of Black residents, based on U.S. Census Bureau American Community Survey data. The results are in Table 12. We observe larger negative effects on exit and deformalization than in the main sample (Panel A columns 1-2, though the effect on deformalization is not significant). There is also a larger positive effect on employment, at 32% relative to 19% in the main results. We also find that the financial effects are larger in high black neighborhoods (Panel B).[34] We find similar results when we use other proxies for local wealth and credit constraints, such as the median level of education and per capital income (not reported).

Last, we ask whether the results are stronger in neighborhoods that were struggling economically after the disaster. Specifically, we construct an indicator for the Census tract having above-median net firm exit during the post-disaster years.[35] We then restrict the analysis to neighborhoods with above-median net exit. Unfortunately, we cannot report the results for below-median net exit due to Census disclosure regulations, and we cannot construct this struggling neighborhoods variable outside of Census, so do not consider the Experian outcomes.

The results, presented in Table 13, are nuanced. Columns 1 and 4 indicate that in these struggling neighborhoods, there is a larger reduction in the likelihood of exit and a much larger and highly significant positive effect on revenue relative to the main results in Panel A of Table 6, suggesting that loans are more useful for preventing exit and enabling revenue growth in these struggling neighborhoods. However, there is now a large positive effect on deformalization (column 2), suggesting that survivors became nonemployers. Consistent with this, the effect on employment is now negative and insignificant (column 3). These results suggest that in neighborhoods which experience particularly severe economic consequences of the disaster, the SBA loan keeps the business afloat, but often at the cost of transitioning to a nonemployer business, with implications for job creation in the community.[36]

Overall, the results in this section indicate that the SBA loans are more useful for firms and places that are more constrained and have more vulnerable populations, which may reflect SBA loans being especially effective at alleviating credit market frictions in these areas following disasters.[37]

[34] All of the results in Table 12 are robust to excluding Louisiana. Louisiana experienced Hurricane Katrina, which particularly affected Black neighborhoods.

[35] To calculate net firm exit, we take the total number of firm exits in each year after the disaster and subtract the total number of firm entry events in that year. Then we take the average of this object across years. We use the zip code in cases where tract is not available.

[36] We find no significant heterogeneity by whether neighborhood was growing or shrinking pre-disaster.

[37] We did not find significant variation in several other mediating variables, such as disaster intensity or type.

8 Conclusion

This paper provides the first causal examination of how government-provided disaster recovery loans affect recipient firms and their local business communities. In theory, disaster loans help businesses regain productivity, spurring local economic recovery. An advantage of the SBA disaster loan program is that it is directly provided from the government to firms, without intermediation fees or incentive alignment concerns. However, it is not immediately obvious that loans will be useful to the recipient businesses, let alone their neighbors. For example, by adding leverage and interest payment burdens to already-struggling firms, they might increase the chances of firm failure. Using survey evidence, Dahlhamer and Tierney (1998) find that following a large earthquake in Los Angeles in 1994, disaster loans were correlated with worse business outcomes because they increased the debt burdens for firms very unlikely to survive regardless.

We employ comprehensive administrative data from the SBA disaster recovery loan program between 2005 and 2017, which we link to both financial and real economic outcomes. Our estimation design relies on discontinuities in approval rates at particular thresholds of the owner's FICO score. We use these to instrument for loan approval, creating a series of natural experiments that effectively randomly assigning credit to businesses around the owner-FICO threshold, enabling local average treatment effect (LATE) estimates. We leverage the annual, panel structure of our data to examine firm outcomes over time, up to seven years after the disaster. One advantage of our setting relative to existing work is the ability to observe application data, which are unavailable for other SBA programs, because banks or other intermediaries administer those programs.

Disaster recovery loans have strong, positive effects on both real and financial outcomes. They reduce the chances of firm exit and transition from an employer to a nonemployer firm, which has implications for future hiring and firm growth. We also see positive effects on employment and revenue, especially among employer firms. These real effects seem in part due to the fact that the loans unlock additional, non-SBA private credit and stave off delinquencies and bankruptcy. Through repairing physical capital, disaster loans may help firms to recover productivity, restore the quality of collateral, or serve as a signal of firm quality to private lenders. All of the effects grow over time and are strongly persistent, indicating that the loans place firms on a different path, permanently reducing the likelihood of exit from the disaster.

We go beyond the recipient firm and study spillover effects on the local community. We find that receiving a loan increases local firm entry. However, there may be negative impacts on the existing neighbors of recipient firms. While we cannot speak to welfare effects, these results relate to the process of creative destruction that is accelerated by a disaster. As new entrants—especially those that are employer firms—are disproportionately responsible for productivity and employment growth (Haltiwanger, 2009; Decker et al., 2014), it seems likely that the overall spillovers are positive.

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Table 1: Summary Statistics of SBA Applicants

Panel A: Applicant Information (Counts)

Applications	167,202
Borrowers	54,532
Total Employees of Borrowers	236,570
Amount Disbursed ($)	5,330,940

Panel B: Approval and Borrowing Frequencies (%)

P(Approved | Applied)	43.9
P(Borrowed | Applied)	32.6

Panel C: Applications by Disaster Type (%)

Hurricane	73.0
Storm / Flood	14.3
Tornado	7.3
Fire	1.4
Drought	1.0
BP Oil Spill	0.9
Other	2.2

Panel D: Applications by Organizational Type (%)

Sole Proprietor/Individual	59
Corporation	23
LLC, LLP, Or LLE	12
NonProfit Organization	4
Partnership	1
Other	1

Panel D: Applications by Industry (%)

Real Estate and Rental and Leasing	32.8
Other Services (except Public Administration)	11.5
Retail Trade	11.3
Accommodation and Food Services	6.7
Professional, Scientific, and Technical Services	5.5
Construction	5.1
Other	27.2

Notes: All dollar amounts are in thousands of $2018. Panel A describes the number of applicants and dollars disbursed. The remaining panels describe respectively the share of applicants by lending and borrowing decisions, disaster type, organizational type, and industry.

Table 2: Summary Statistics for SBA Applicants by Approval Status

	Mean	Std. Dev	p10	Median	p90	Observations
Panel A: All Applicants						
	(1)	(2)	(3)	(4)	(5)	(6)
Age	13.1	34.2	1.0	8.0	29.0	138,284
Employees	4.7	11.1	0.0	1.0	10.0	120,403
FICO Score	618.5	154.0	487.0	638.0	782.0	83,956
Loss Amount	156.4	833.9	6.9	46.8	308.4	102,995
Panel B: Declined Applicants						
	Mean	Std. Dev	p10	Median	p90	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Age	11.7	38.7	1.0	6.0	26.0	76,262
Employees	3.8	10.0	0.0	1.0	8.0	65,302
FICO Score	564.7	159.5	460.0	573.0	733.0	50,127
Loss Amount	124.6	855.3	4.8	33.8	236.3	42,577
Panel C: Approved Applicants						
	Mean	Std. Dev	p10	Median	p90	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Age	14.8	27.7	2.0	10.0	32.0	62,022
Employees	5.7	12.1	0.0	2.0	13.0	55,101
FICO Score	698.1	102.8	603.0	707.0	799.0	33,829
Loss Amount	178.9	817.8	9.2	58.1	355.9	60,418
Amount Disbursed	72.7	209.4	0.0	18.4	179.9	73,361
Interest Rate	3.8	0.7	2.9	4.0	4.0	73,361
Maturity (years)	18.9	10.1	5.0	16.8	30.0	73,361
Monthly Payments	0.7	2.3	0.1	0.3	1.4	73,361

Notes: All dollar amounts are in thousands of $2018. Firm age is in years.

Table 3: Summary Statistics for Census Firms

Panel A: Sample Characteristics

	Mean (1)	Std. Dev (2)	Quasimedian (3)	Observations (4)
Post Disaster	0.51			291,000
Approved	0.34			291,000
Post Disaster x Approved	0.17			291,000
Firm Age	11.3	29.3	7.00	291,000
Black Population Share	0.23			291,000

Panel B: Experian Sample Characteristics

	Mean (1)	Std. Dev (2)	Median (3)	Observations (4)
Post Disaster	0.62	0.49	1	262847
Approved	0.39	0.49	0	262847
Post Disaster x Approved	0.24	0.43	0	262847
Firm Age	11.4	60.4	7	255710
Black Population Share	0.22	0.26	0.10	239634

Panel C: Census Real Outcomes

	Mean (1)	Std. Dev (2)	Quasimedian (3)	Observations (4)
Exit	0.12			291,000
Deformalization	0.06			170,000
Number of Employees	2.99	4.37	1.00	170,000
Revenue	351	592	72.9	128,000

Note: "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008.

Table 4: Summary Statistics for Experian Financial Outcomes

Panel A: Private Credit Outcomes (Experian Sample)

	Mean (1)	Std. Dev. (2)	Median (3)	Observations (4)
Outstanding Debt	7.93	20.9	0	142199
Outstanding Debt Reported Last 30 Days	4.43	13.7	0	142199
Number of Contracts	0.49	0.82	0	142199
Delinquent Share of Debt	0.13	0.32	0	53959
Days Late on all Contracts	16.7	34.5	0	53959
Bankruptcy	0.028	0.16	0	142876

Panel B: Private Credit Outcomes (Experian Sample, Conditional on Matching to Census)

	Mean (1)	Std. Dev. (2)	Quasimedian (3)	Observations (4)
Outstanding Debt	10.0	24.5	0.00	62,000
Outstanding Debt Reported Last 30 Days	6.40	17.0	0.00	62,000
Number Trades with Contracts	0.56	0.91	0.00	62,000
Delinquent Share of Debt	0.08	0.26	0.00	28,000
Days Late on all Contracts	5.08	19.6	0.00	62,000
Bankruptcy	0.01			62,000

Note: Experian variables are drawn from a June 30 snapshot. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Days” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008.

Table 5: Summary Statistics for Form of Firm Exit in Experian Sample Matched to Census

Panel A: All Firms

Dependent Variable:	Mean (1)	Observations (2)
Exit, Overall	0.15	112,000
Exit, Any Bankruptcy	0.01	112,000
Exit, Any Deliquency	0.03	112,000
Exit, Other	0.11	112,000

Panel B: Firms Post Disaster

Dependent Variable:	Mean (1)	Observations (2)
Exit, Overall	0.21	78,000
Exit, Any Bankruptcy	0.01	78,000
Exit, Any Deliquency	0.04	78,000
Exit, Other	0.16	78,000

Panel C: Approved Firms Post Disaster

Dependent Variable:	Mean (1)	Observations (2)
Exit, Overall	0.17	35,000
Exit, Any Bankruptcy	0.01	35,000
Exit, Any Deliquency	0.04	35,000
Exit, Other	0.13	35,000

Note: Experian variables are drawn from a June 30 snapshot. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008.

Table 6: Effect of Disaster Loans on Real Outcomes (2SLS)

Panel A: Real Outcomes (Census Sample, All Firms)

Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.132***	-0.0515*	0.170**	0.196
	(0.0413)	(0.0281)	(0.0831)	(0.143)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.115	0.059	1.042	4.384
Observations	291,000	170,000	170,000	128,000
KP F-Stat	157.2	81.3	81.3	115.5

Panel B: Real Outcomes on Employers (Census Sample, Employer Firms Only)

Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.169***	-0.121**	0.376**	0.719***
	(0.0641)	(0.0503)	(0.183)	(0.254)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.084	0.056	1.413	6.025
Observations	107,000	85,000	85,000	51,000
KP F-Stat	45.28	27.96	27.96	27.56

Note: This table contains estimates of Equation 2. "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Effect of Disaster Loans on Private Credit (2SLS)

Panel A: Credit Outcomes (Experian Sample)

Dependent Variable:	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)
Post Disaster x Approved (IV)	17.712***	9.031***	0.568***
	(3.432)	(2.078)	(0.089)
Application FE	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes
Mean Dep Var	7.934	4.429	0.488
Observations	142,199	142,199	142,199
KP F-Stat	61.461	61.461	61.461

Panel B: Survivor Credit Outcomes
(Experian Sample, Conditional on Match to Census and Never Exiting as of 2019)

Dependent Variable:	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)
Post Disaster x Approved (IV)	17.220***	7.438**	0.523***
	(5.366)	(2.928)	(0.154)
Application FE	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes
Mean Dep Var	10.00	6.40	0.556
Observations	62,000	62,000	62,000
KP F-Stat	47.01	47.01	47.01

Note: This table contains estimates of Equation 2. Experian variables are drawn from a June 30 snapshot. "Outstanding Private Debt" and "Outstanding Private Debt Reported Last 30 Day" are total private credit balances (and do not include the SBA loan). They are in thousands of $2018."Number of Contracts" is a holistic measure of the firm's time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effect of Disaster Loans on Adverse Financial Outcomes (2SLS)

Panel A: Credit Outcomes (Experian Sample)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy
	(1)	(2)	(3)
Post Disaster x Approved (IV)	-0.339***	-34.996***	-0.038*
	(0.086)	(9.676)	(0.022)
Application FE	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes
Mean Dep Var	0.134	16.675	0.028
Observations	53,959	53,959	142,876
KP F-Stat	14.835	14.835	61.142

Panel B: Survivor Credit Outcomes
(Experian Sample Conditional on Matching to Census and Never Exiting as of 2019)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy
	(1)	(2)	(3)
Post Disaster x Approved (IV)	-0.165	-7.082	-0.00994
	(0.111)	(4.459)	(0.0222)
Application FE	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes
Mean Dep Var	0.083	5.085	0.014
Observations	28,000	62,000	62,000
KP F-Stat	13.60	47.01	47.01

Note: This table contains estimates of Equation 2. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Effect of Disaster Loans on Form of Firm Exit (2SLS)

Panel A: Exit Outcomes (Experian Sample Matched to Census)

	Form of Exit			
Dependent Variable:	Overall	Bankruptcy	Delinquency	Other
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.145***	-0.0178	-0.0150	-0.110**
	(0.0544)	(0.0128)	(0.0246)	(0.0468)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.149	0.007	0.030	0.115
Observations	112,000	112,000	112,000	112,000
KP F-Stat	67.25	67.25	67.25	67.25

Panel B: Employer Exit Outcomes (Experian Sample Matched to Census, Employer Firms Only)

	Form of Exit			
Dependent Variable:	Overall	Bankruptcy	Delinquency	Other
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.0969*	-0.0407**	0.00632	-0.0725
	(0.0562)	(0.0182)	(0.0365)	(0.0445)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.112	0.009	0.032	0.074
Observations	60,000	60,000	60,000	60,000
KP F-Stat	39.75	39.75	39.75	39.75

Note: This table contains estimates of Equation 2. Experian variables are drawn from a June 30 snapshot. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Spillovers: Disaster Loan Effects on Local Entry and Incumbent Neighbor Firms (2SLS)

Panel A: Real Outcomes (Census Sample with LBD Neighbors)

Dependent Variable:	Neighborhood Entry (if $\geq$ 3 Employees)	Exit	Deformalization	Log Employment	Log Revenue
		Incumbent Neighbor Firms			
	(1)	(2)	(3)	(4)	(5)
Post Disaster x Approved (IV)	7.901*	-0.0102	0.00372	-0.0414	-0.227*
	(4.382)	(0.0235)	(0.00269)	(0.0494)	(0.130)
Application FE	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	1.336	0.076	0.003	1.781	8.053
Observations	130,000	914,000	914,000	691,000	691,000
KP F-Stat	97.41				

Panel B: Financial Outcomes (Experian Sample with D&B Neighbors)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)	(4)	(5)	(6)
Post Disaster x Approved (IV)	0.219	20.684	0.021	4.528	5.485	-0.102
	(0.150)	(15.780)	(0.056)	(4.578)	(4.744)	(0.395)
Application FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	0.096	13.262	0.020	5.150	4.775	0.424
Observations	27,797	27,797	90,438	89,851	89,851	89,851
KP F-Stat	5.877	5.877	7.820	7.516	7.516	7.516

Note: This table contains estimates of Equation 2. “Neighborhood Entry” is measured as the difference between the number of firms in the tract in year t and year $t-1$. “Exit” is a binary variable equal to 1 after a firm has permanently exited from the sample. “Deformalization” marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Variation in Disaster Loan Effects Around Median Firm Age at Application (2SLS)

Panel A: Real Outcomes (Census Sample)

	Older Firms		Young Firms	
Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.175***	-0.0805*	0.246**	0.624**
	(0.0522)	(0.0443)	(0.0956)	(0.262)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.102	0.070	0.935	3.990
Observations	140,000	94,000	76,000	56,000
KP F-Stat	156.5	80.3	35.4	38.0

Panel B: Credit and Adverse Financial Outcomes for Young Firms (Experian Sample)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)	(4)	(5)	(6)
Post Disaster x Approved (IV)	-0.385**	-33.556**	-0.056*	9.980**	2.322	0.280**
	(0.172)	(16.422)	(0.030)	(3.908)	(2.075)	(0.112)
Application FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	0.11	13.76	0.01	4.93	1.47	0.33
Observations	15,005	15,005	61,337	61,337	61,337	61,337
KP F-Stat	8.42	8.42	29.98	29.98	29.98	29.98

Panel C: Credit and Adverse Financial Outcomes for Old Firms (Experian Sample)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)	(4)	(5)	(6)
Post Disaster x Approved (IV)	-0.215**	-23.554**	0.014	15.068***	9.440***	0.586***
	(0.085)	(9.947)	(0.028)	(4.677)	(3.367)	(0.145)
Application FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	0.15	17.89	0.04	10.45	6.88	0.62
Observations	35,422	35,422	76,825	76,147	76,147	76,147
KP F-Stat	15.52	15.52	52.49	52.82	52.82	52.82

Note: This table contains estimates of Equation 2. Young firms are those 7 years or younger. “Exit” is a binary variable equal to 1 after a firm has permanently exited from the sample. “Deformalization” marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Disaster Loan Effects in Neighborhoods with Above-Median Black Populations (2SLS)

Panel A: Real Outcomes (Census Sample)

Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.175***	-0.0886	0.277**	0.122
	(0.0602)	(0.0551)	(0.127)	(0.340)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.129	0.057	0.989	4.080
Observations	145,000	76,000	76,000	59,500
KP F-Stat	86.66	31.95	31.95	35.41

Panel B: Credit and Adverse Financial Outcomes (Experian Sample)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)	(4)	(5)	(6)
Post Disaster x Approved (IV)	-0.473***	-49.037***	-0.058	19.006***	10.283***	0.328**
	(0.115)	(12.636)	(0.036)	(5.250)	(2.543)	(0.164)
Application FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	0.155	18.827	0.020	7.016	3.816	0.448
Observations	24,621	24,621	68,189	68,097	68,097	68,097
KP F-Stat	10.922	10.922	30.971	30.979	30.979	30.979

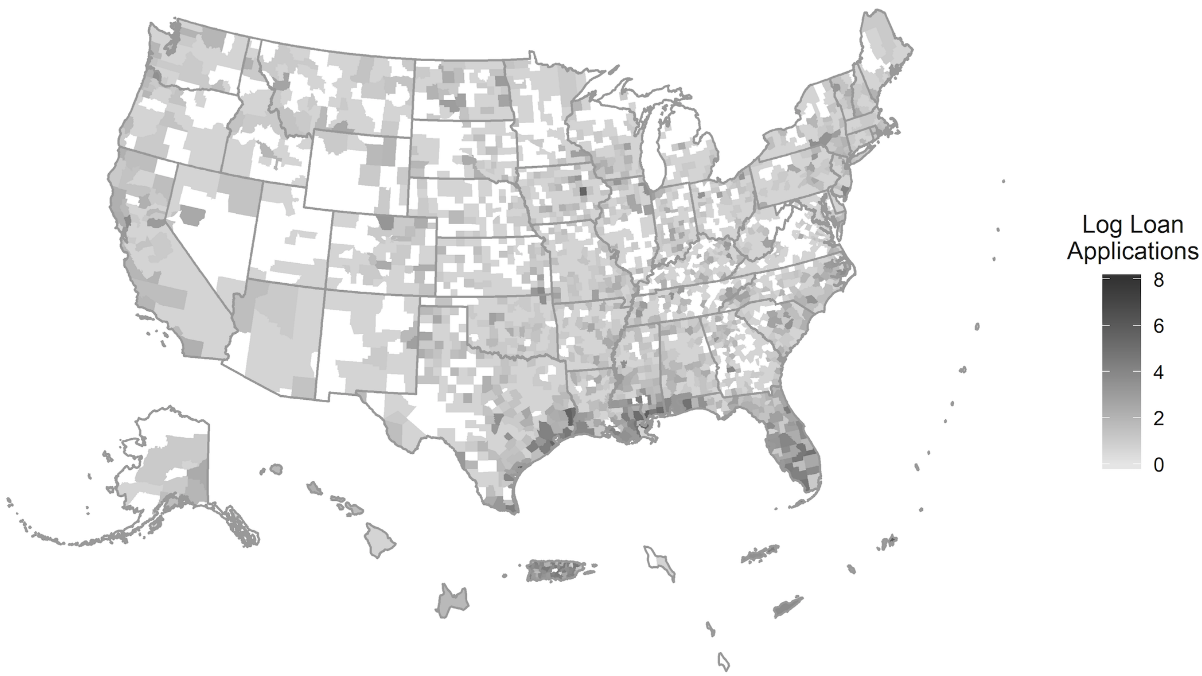
Note: This table contains estimates of Equation 2. "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. "Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. "Bankruptcy" is identified by any type of bankruptcy filing. "Outstanding Private Debt" and "Outstanding Private Debt Reported Last 30 Day" are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. "Number of Contracts" is a holistic measure of the firm's time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Disaster Loan Effects in Struggling Neighborhoods (2SLS)

Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved (IV)	-0.171***	0.225*	-0.0669	0.455**
	(0.0569)	(0.134)	(0.0421)	(0.203)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.118	0.062	1.067	4.481
Observations	148,000	88,000	88,000	64,500
KP F-Stat	151.0	62.64	62.64	27.56

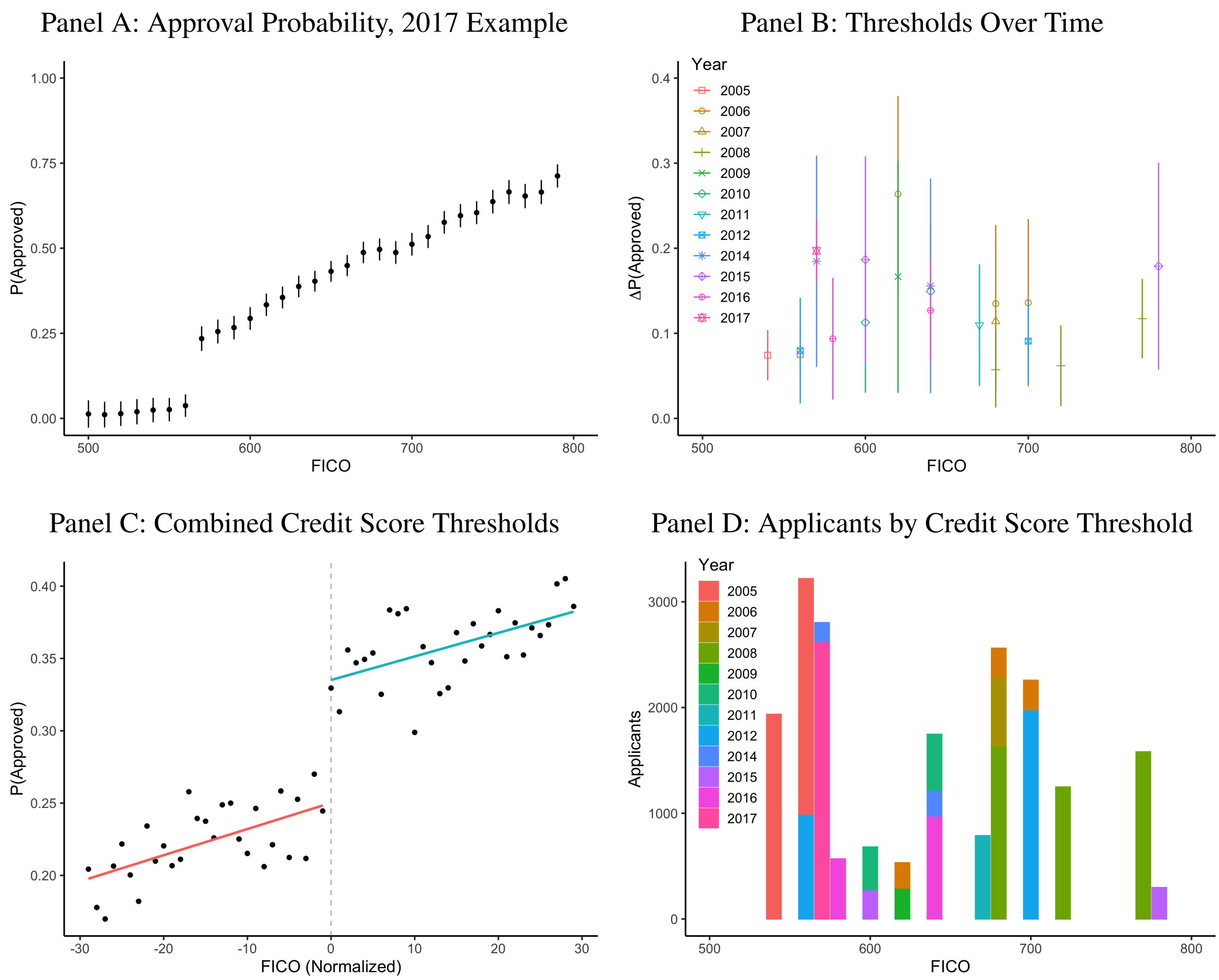
Note: This table contains estimates of Equation 2, restricting the sample to neighborhoods (defined at the tract level) with above-median net firm exit post-disaster. "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Standard errors are clustered by FEMA disaster declaration ID. "Outstanding Private Debt" and "Outstanding Private Debt Reported Last 30 Day" are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 1: Geographic Dispersion of Applications



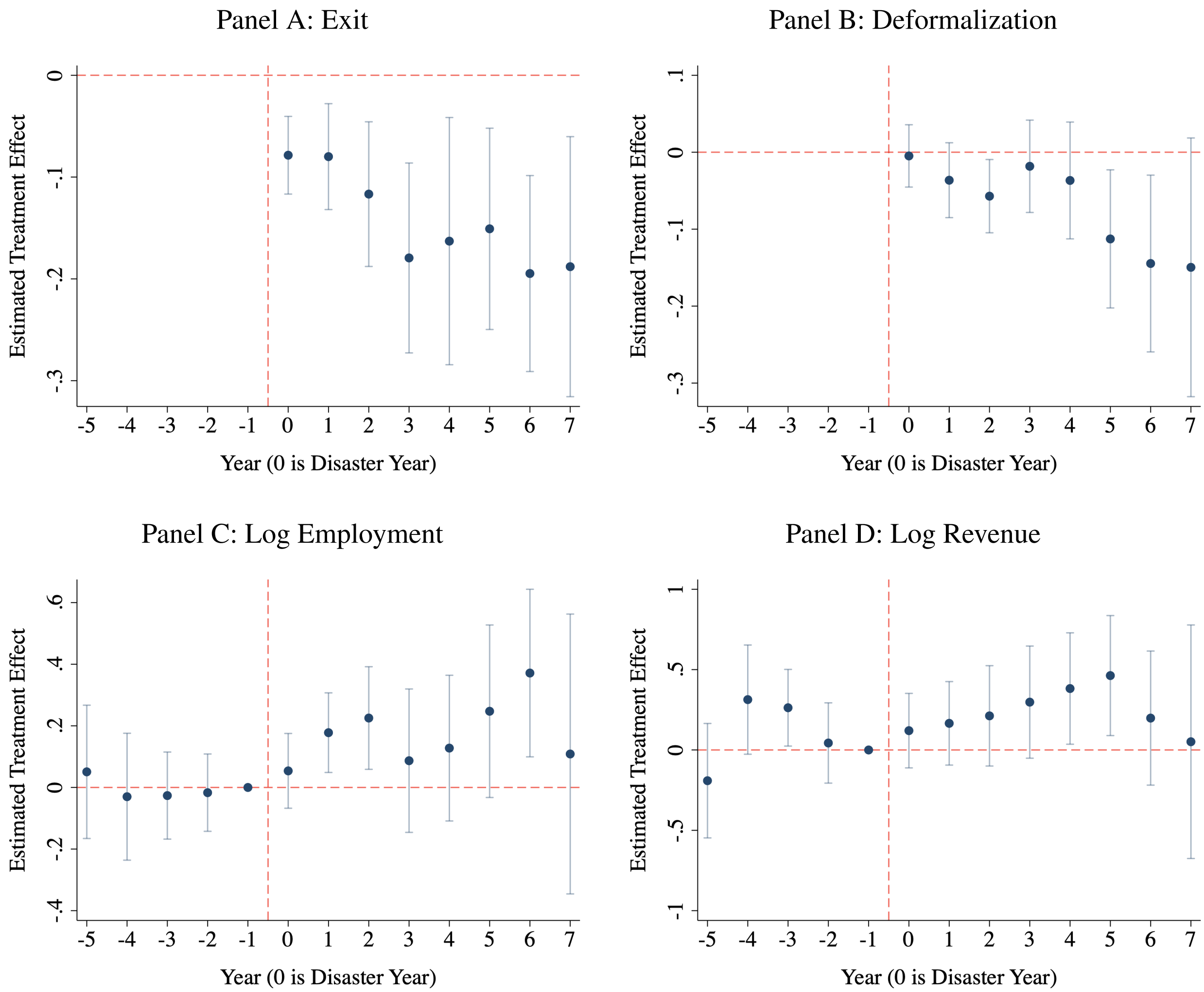
Note: This map shows the log number of applications by county for the U.S. and the territories.

Figure 2: Loan Approval and Credit Score



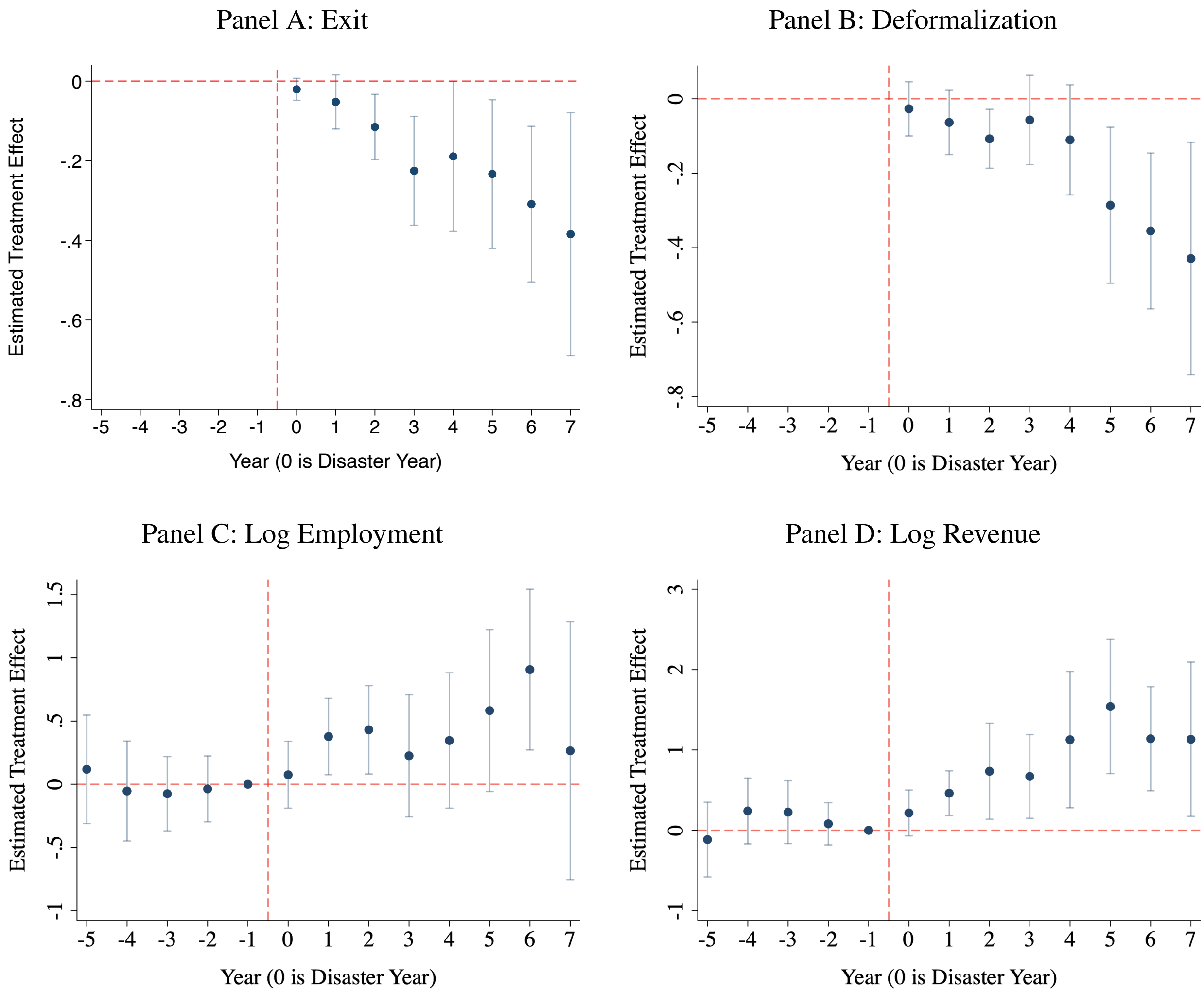
Note: The figure shows the relationship between credit score and approval probability. Panel (a) is an illustration, showing that having a FICO score of at least 570 is an important predictor of approval for applicants who experienced a disaster in 2017. The plot reports the coefficients from a regression of whether an applicant was approved on binned FICO scores. Figure A2 in the Online Appendix shows a similar plot for each year. Panel (b) shows the 22 credit score discontinuities used in the analyses. The vertical axis reports the change in approval probability at the threshold. Panel (c) combines data from 22 identified credit score thresholds between 2005 and 2018, normalizing FICO scores so that FICO = 0 at the threshold. Panel (d) shows the number of applicants by credit score discontinuity.

Figure 3: Effect of Disaster Loans on Real Outcomes



Note: These figures contain estimates of Equation 3. "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this figure were disclosed under DRB CBDRB-FY23-CED006-0008.

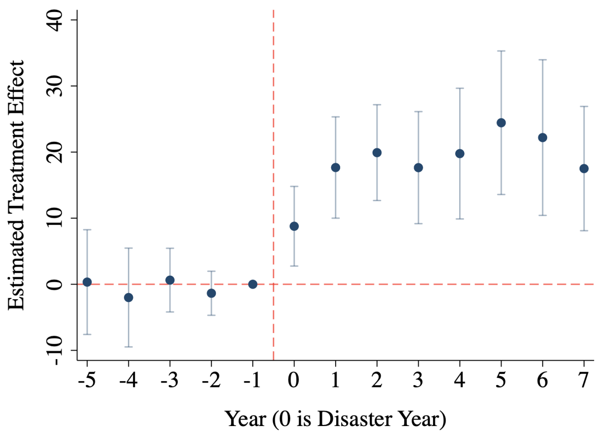
Figure 4: Effect of Disaster Loans on Real Outcomes (Census Sample, Employer Firms Only)



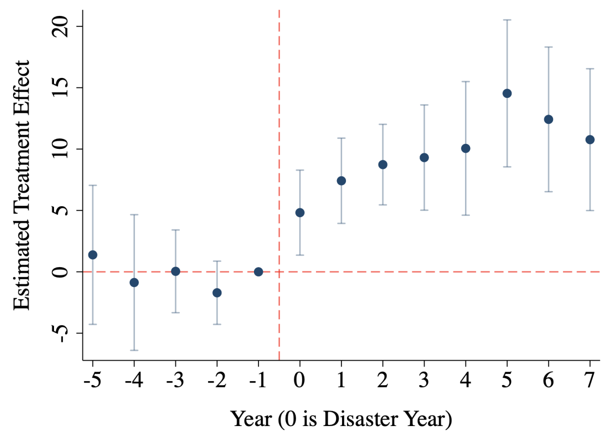
Note: These figures contain estimates of Equation 3. "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this figure were disclosed under DRB CBDRB-FY23-CED006-0008.

Figure 5: Event Study Effect of Disaster Loans on Private Credit

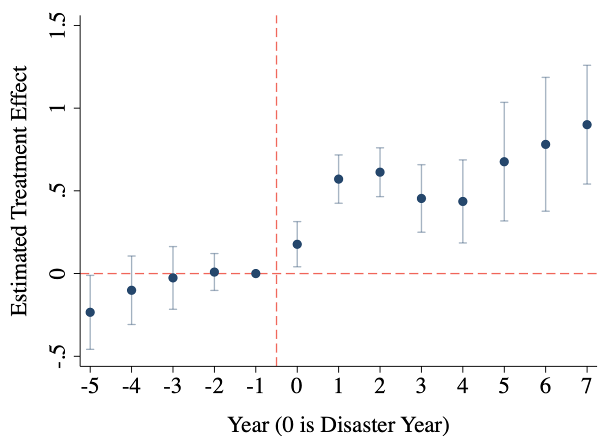
Panel A: Outstanding Private Debt



Panel B: Outstanding Private Debt Reported Last 30 Days



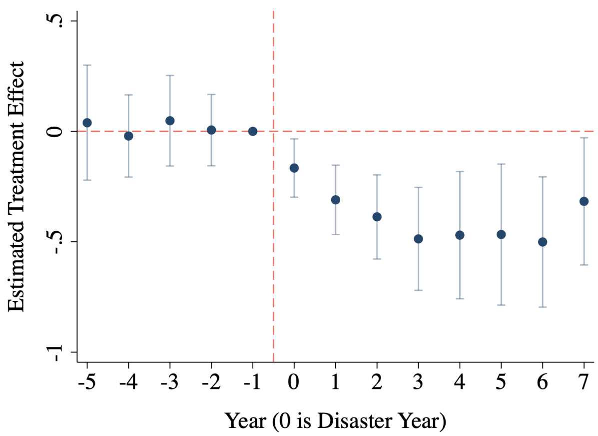
Panel C: Number of Contracts



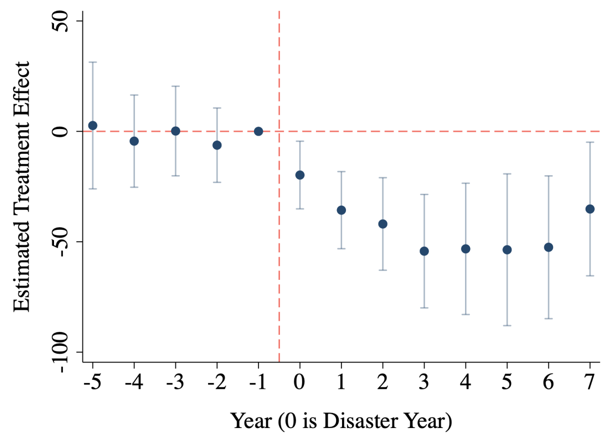
Note: These figures contain estimates of Equation 3. Experian variables are drawn from a June 30 snapshot. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others.

Figure 6: Event Study Effect of Disaster Loans on Adverse Financial Outcomes

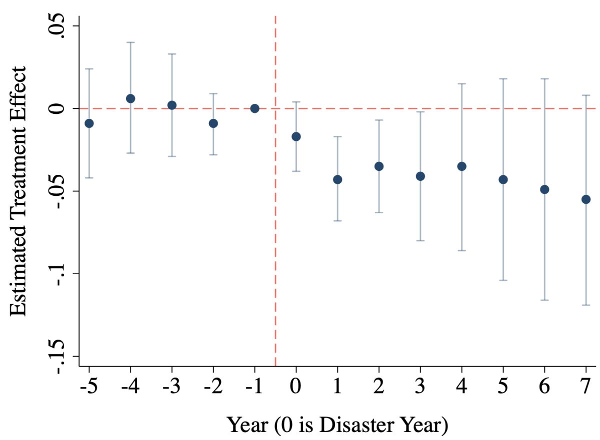
Panel A: Delinquent Share of Debt



Panel B: Days Late on all Contracts



Panel C: Bankruptcy



Note: These figures contain estimates of Equation 3. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing.

Appendix A Appendix: Regression Discontinuity, Additional Details

Table A1 shows regression estimates of how the threshold affects approval likelihood in models controlling for the running variable and fixed effects for ZIP code and disaster year by FICO threshold.

Table A1: Regression of Approval Likelihood on Threshold, Bandwidth 29

Dependent Variable: $\mathbb{1}(Approved)$

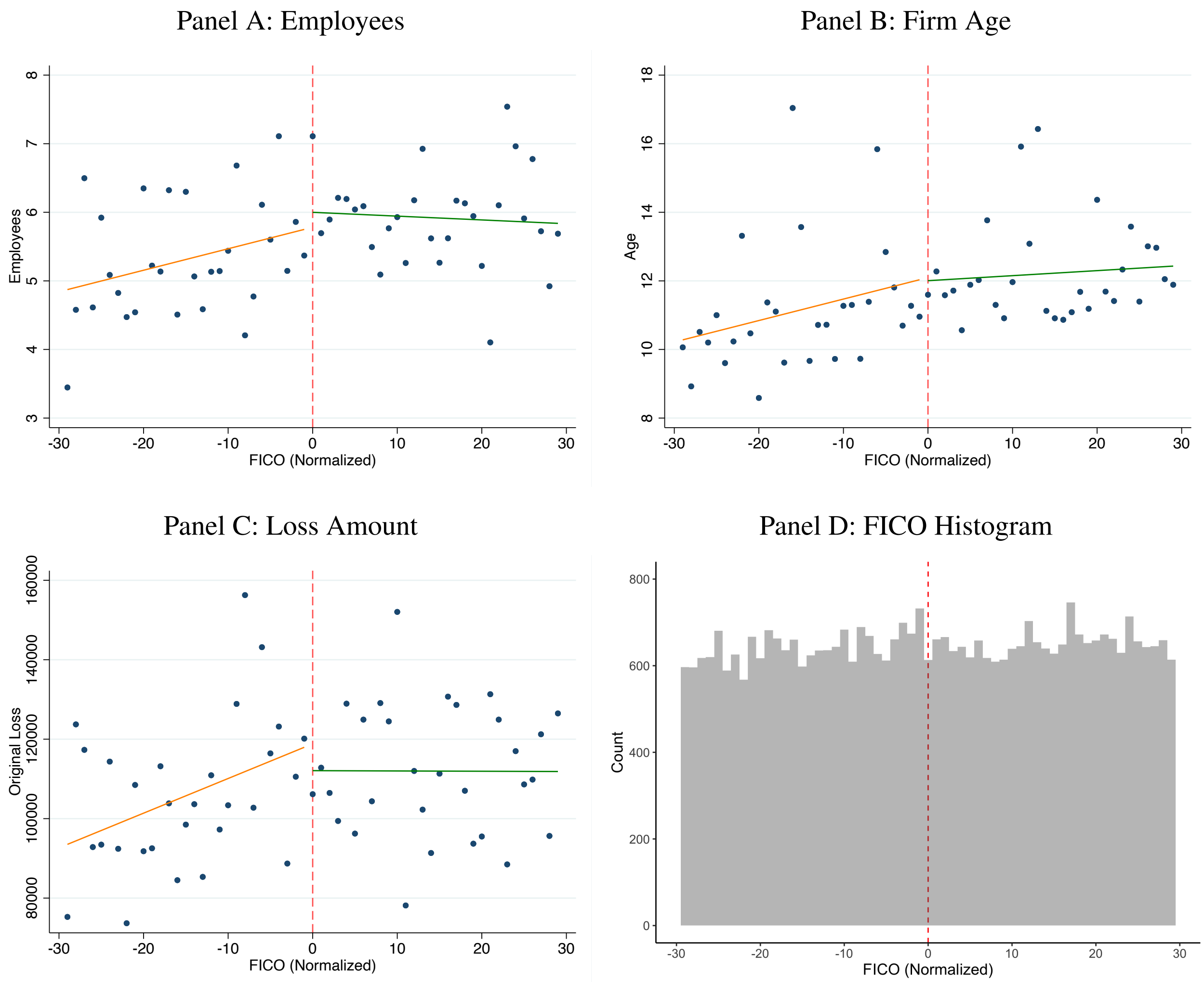
	(1)	(2)	(3)	(4)
$\mathbb{1}(FICO \geq 0)$	0.149***	0.096***	0.128***	0.120***
	(0.017)	(0.016)	(0.018)	(0.021)
$\mathbb{1}(FICO < 0) \times FICO$		0.002***	-0.005*	-0.002
		(0.001)	(0.003)	(0.002)
$\mathbb{1}(FICO < 0) \times FICO^2$			-0.000***	-0.000
			(0.000)	(0.000)
$\mathbb{1}(FICO \geq 0) \times FICO$		0.002***	0.002	-0.001
		(0.001)	(0.002)	(0.002)
$\mathbb{1}(FICO \geq 0) \times FICO^2$			0.000	0.000**
			(0.000)	(0.000)
Disaster Year × Threshold FE	No	No	No	Yes
Zip FE	No	No	No	Yes
Clustered SE	Disaster ID	Disaster ID	Disaster ID	Disaster ID
R^2	0.023	0.024	0.025	0.303
Within R^2	0.023	0.024	0.025	0.019
N	20,219	20,219	20,219	20,219

Figure A1 examines the continuity of firm characteristics through the threshold (Panels A - C) and the count of firms through the threshold as a sorting test.

Table A2 reports the FICO thresholds used in the analyses. In a couple of cases, two thresholds are nearby in the same year (e.g., FICO 540 and 560 in 2005), resulting in around 1% of observations that could be assigned to either threshold. In these cases, we associate the firm with the closest threshold.

Figure A2 reports the results of regressing the likelihood of approval on FICO score for each year. The panels show the change in approval likelihood relative to a reference group of applicants with FICO scores of at least 800.

Figure A1: Threshold Continuity

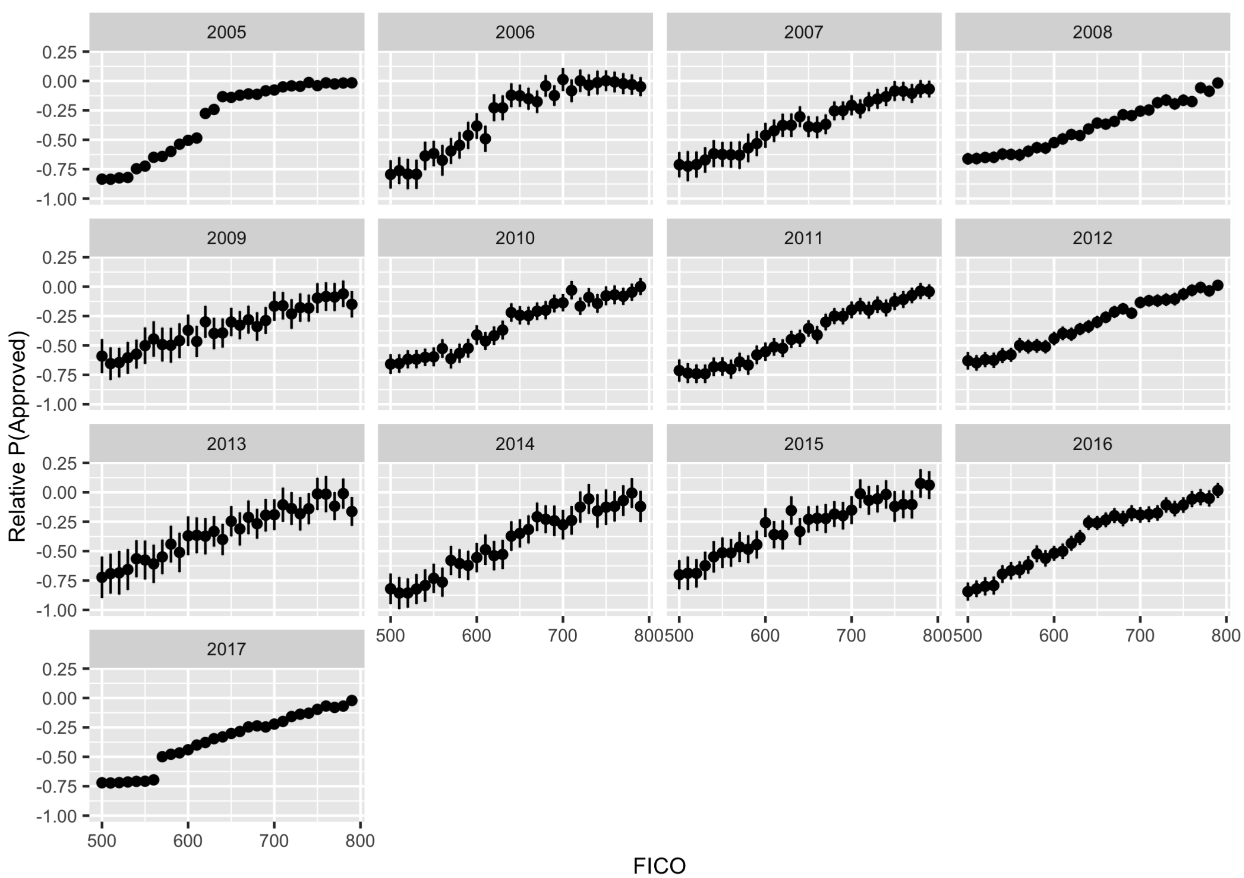


Note: The figure shows the number of employees, firm age, disaster-related loss amount, and count of firms across values of normalized credit score.

Table A2: Credit Score Thresholds Over Time

FICO	Years		
540	2005		
560	2005	2012	
570	2014	2017	
580	2016		
600	2010	2015	
620	2006	2009	
640	2010	2014	2016
670	2011		
680	2006	2007	2008
700	2006	2012	
720	2008		
770	2008		
780	2015		

Figure A2: Credit Discontinuities by Year



Appendix B   Appendix: Summary Statistics

Table B1: Summary Statistics for Census Firms

Panel A: Census Incumbent Neighbors

	Mean	Std. Dev	Quasimedian	Observations
	(1)	(2)	(3)	(4)
Neighborhood Entry	1.19	25.92	0.00	231,000
Exit	0.08			914,000
Deformalization	0.003			914,000
Number of Employees	9.79	9.77	5.50	691,000
Revenue	625,000	1,864,000	945	543,000

Note: “Exit” is a binary variable equal to 1 after a firm has permanently exited from the sample. “Deformalization” marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008.

Appendix C Appendix: Robustness Results

Table C1: Effect of Disaster Loans Estimated using OLS

Panel A: Real Outcomes (Census Sample)

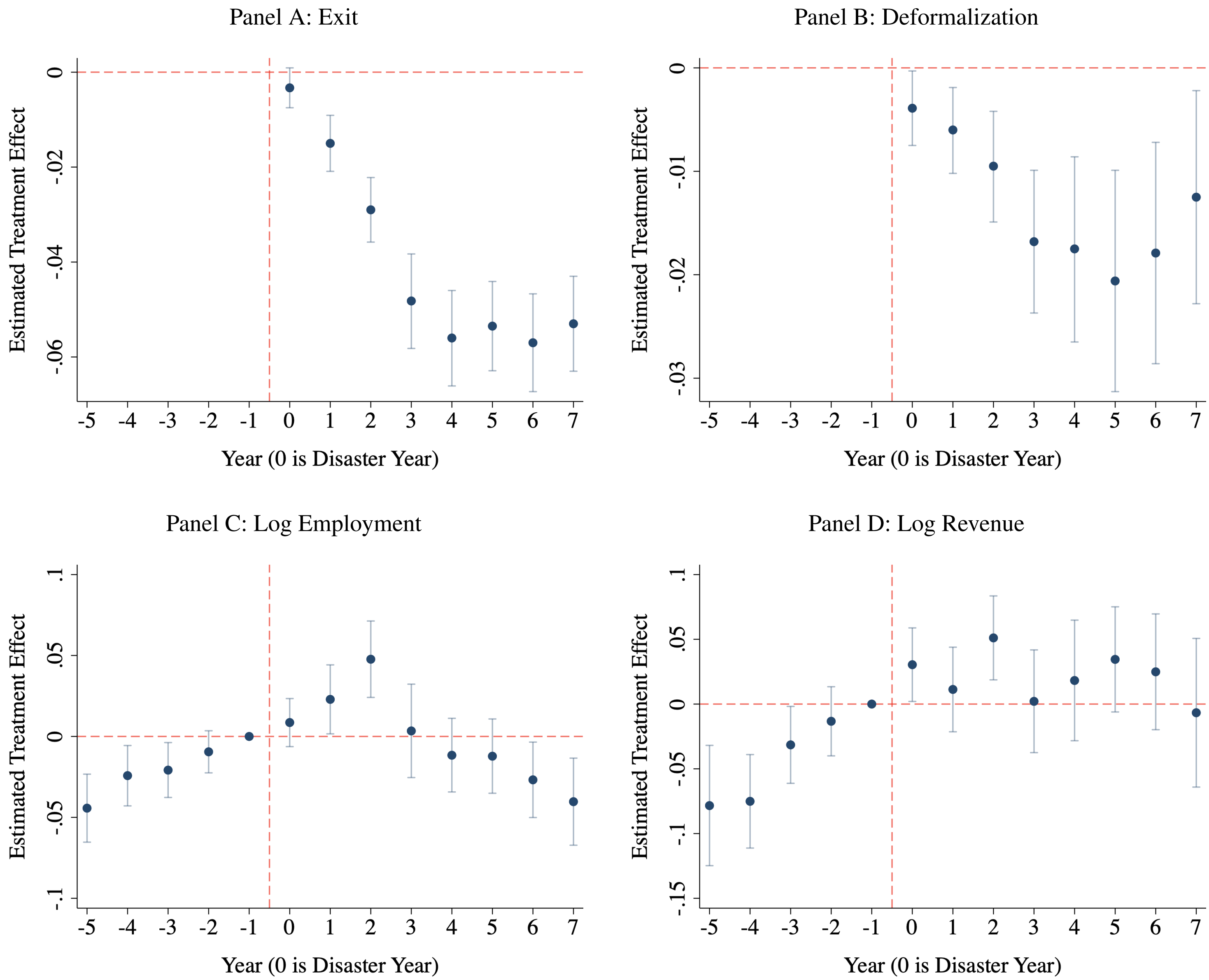
Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved	-0.0414***	-0.0116***	0.0182*	0.0471***
	(0.00379)	(0.00334)	(0.0105)	(0.0182)
Application FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.115	0.059	1.042	4.384
Observations	291,000	170,000	170,000	128,000

Panel B: Credit and Adverse Financial Outcomes (Experian Sample)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)	(4)	(5)	(6)
Post Disaster x Approved	-0.054***	-6.944***	-0.012***	11.931***	6.337***	0.543***
	(0.011)	(1.179)	(0.003)	(0.857)	(0.401)	(0.023)
Application FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	0.134	16.675	0.028	7.934	4.429	0.488
Observations	53,959	53,959	142,876	142,199	142,199	142,199

Note: This table contains estimates of Equation 1. “Exit” is a binary variable equal to 1 after a firm has permanently exited from the sample. “Deformalization” marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

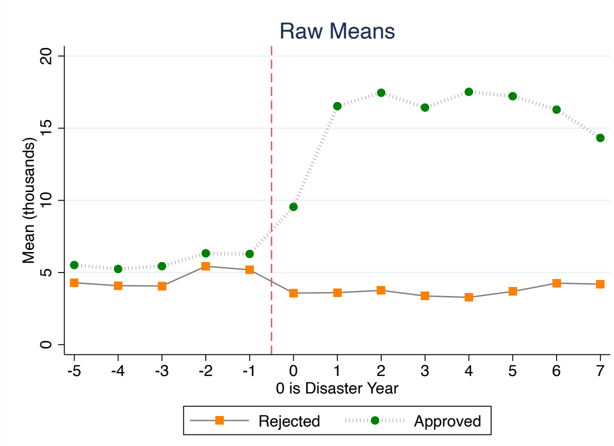
Figure C1: Effect of Disaster Loans on Real Outcomes, OLS



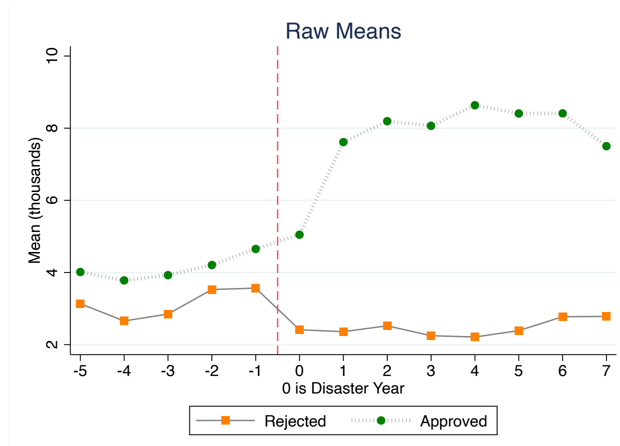
Note: These figures contain estimates of Equation 3. "Exit" is a binary variable equal to 1 after a firm has permanently exited from the sample. "Deformalization" marks a permanent transition from an employer firm to a non-employer firm. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this figure were disclosed under DRB CBDRB-FY23-CED006-0008.

Figure C2: Raw Means For Private Credit

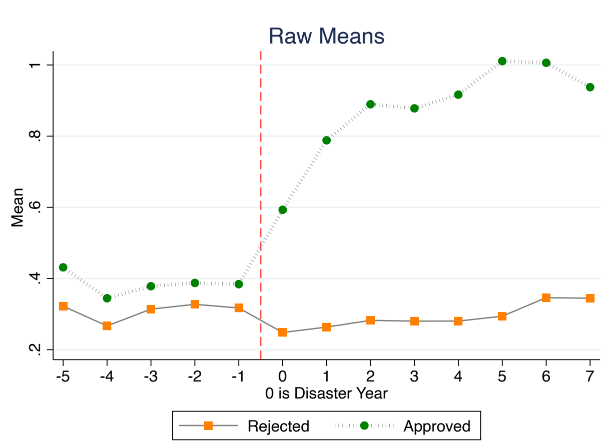
Panel A: Outstanding Debt



Panel B: Outstanding Debt Reported Last 30 Days



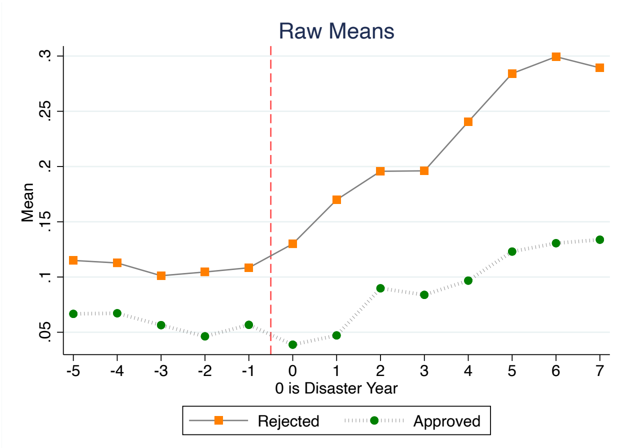
Panel C: Number of Contracts



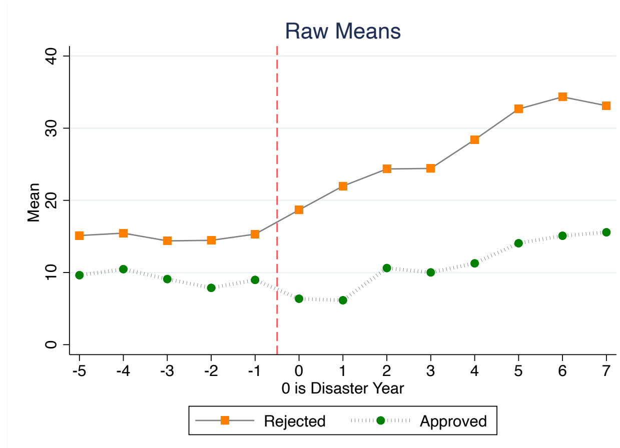
Note: These figures show average values for approved and rejected applicants by year. Experian variables are drawn from a June 30 snapshot. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others.

Figure C3: Raw Means For Adverse Financial Outcomes

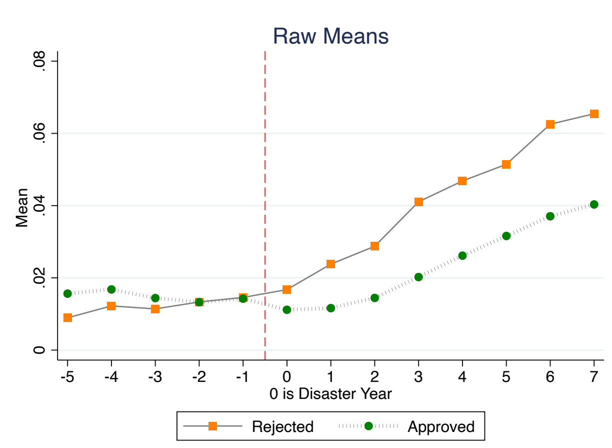
Panel A: Delinquent Share of Debt



Panel B: Days Late on all Contracts

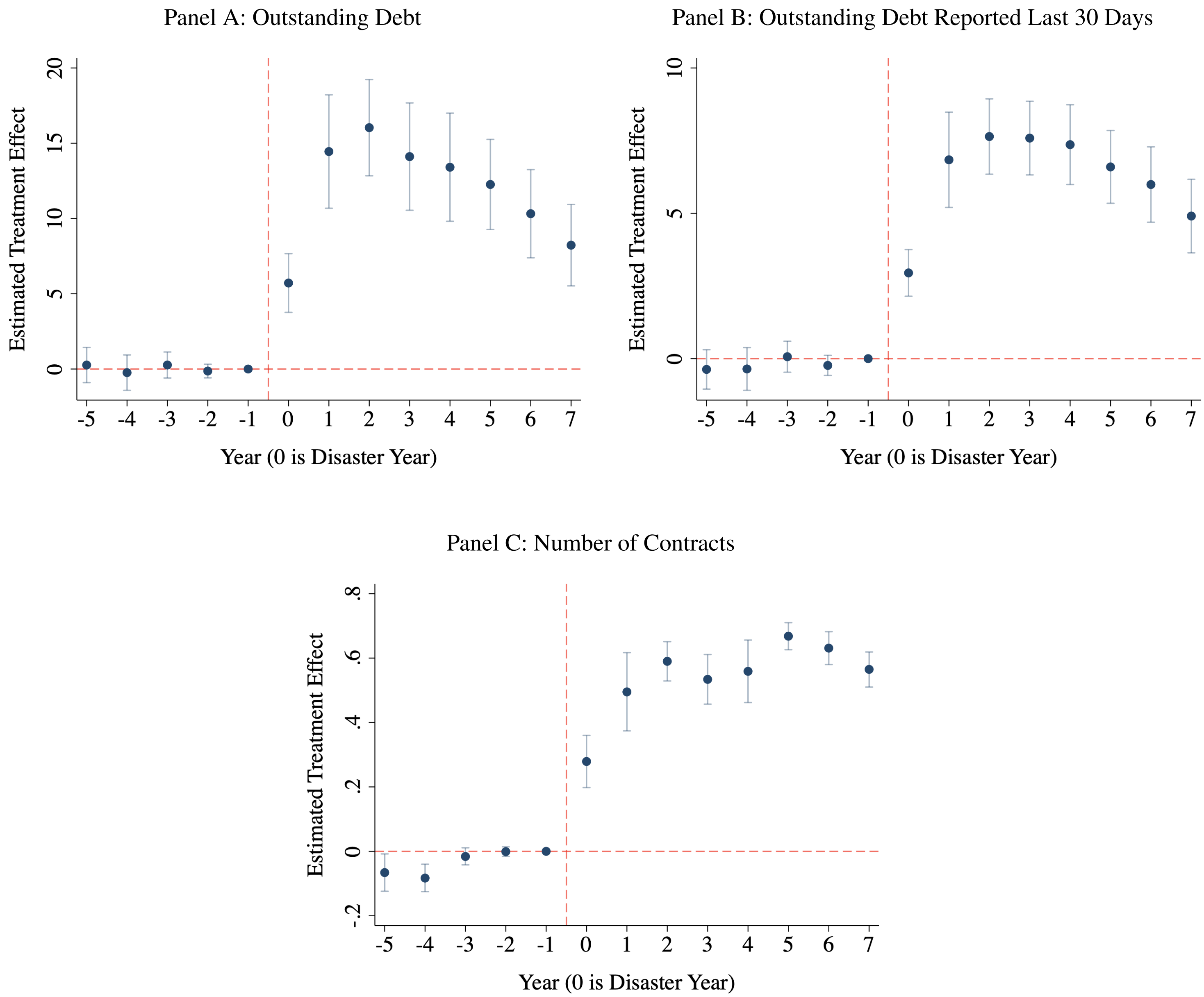


Panel C: Bankruptcy



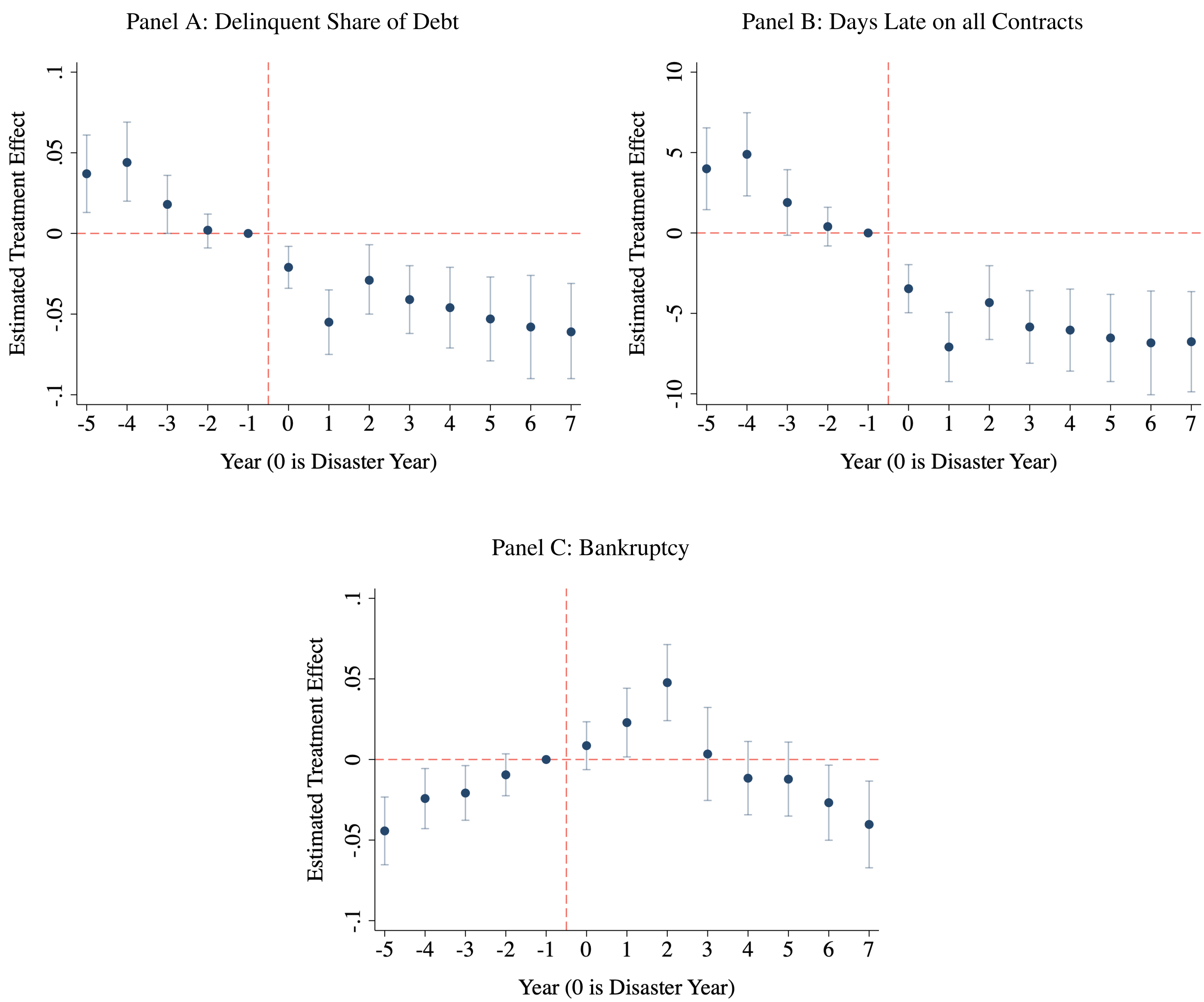
Note: These figures show average values for approved and rejected applicants by year. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing.

Figure C4: Effect of Disaster Loans on Private Credit, OLS



Note: These figures contain estimates of Equation 3. Experian variables are drawn from a June 30 snapshot. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others.

Figure C5: Effect of Disaster Loans on Adverse Financial Outcomes, OLS



Note: These figures contain estimates of Equation 3. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing.

Table C2: Disaster Loan Effects Estimated using Zipcode Fixed Effects (2SLS)

Panel A: Real Outcomes (Census Sample)

Dependent Variable:	Exit	Deformalization	Log Employment	Log Revenue
	(1)	(2)	(3)	(4)
Post Disaster x Approved	-0.134***	-.055	.1944	.0779
	(0.0475)	(0.0342)	(0.1189)	(0.3052)
Zipcode FE	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes
Mean Dep Var	0.115	0.059	1.042	4.384
Observations	291,000	170,000	170,000	128,000
KP F-Stat	163.5	97.1	97.1	128.1

Panel B: Credit and Adverse Financial Outcomes (Experian Sample)

Dependent Variable:	Delinquent Share of Debt	Days Late on all Contracts	Bankruptcy	Outstanding Private Debt	Outstanding Private Debt Reported Last 30 Days	Number of Contracts
	(1)	(2)	(3)	(4)	(5)	(6)
Post Disaster x Approved	-0.246***	-25.933***	-0.026	14.940***	5.332***	0.461***
	(0.088)	(9.341)	(0.022)	(2.833)	(1.746)	(0.096)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Yr x Threshold x Disaster Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	0.134	16.675	0.028	7.934	4.429	0.488
Observations	53,959	53,959	142,876	142,199	142,199	142,199

Note: This table contains estimates of Equation 2. “Exit” is a binary variable equal to 1 after a firm has permanently exited from the sample. “Deformalization” marks a permanent transition from an employer firm to a non-employer firm. Experian variables are drawn from a June 30 snapshot. “Delinquent Share of Debt" is the share of outstanding debt that has been reported delinquent for at least 90 days "Days Late on all Contracts" is the number of days late (i.e., beyond the payment deadline) for all contracts. “Bankruptcy” is identified by any type of bankruptcy filing. “Outstanding Private Debt” and “Outstanding Private Debt Reported Last 30 Day” are total private credit balances (and do not include the SBA loan). They are in thousands of $2018. “Number of Contracts" is a holistic measure of the firm’s time-sensitive obligations including private credit contracts but also leases, utilities, and telecom, among others. Standard errors are clustered by FEMA disaster declaration ID. Estimates in this table were disclosed under DRB CBDRB-FY23-CED006-0008. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.