Financing Negative Shocks: Evidence from Hurricane Harvey*

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Abstract

Financing frictions may limit the risk management of businesses, increasing their vulnerability to shocks. We examine business financing outcomes following Hurricane Harvey. Our analyses use two novel datasets on private companies: the credit reports of 8,219 businesses and a survey of 273 local firms. We address two questions in our analyses. First, to what extent did Harvey cause firms financial distress? Using their exact street addresses, we match businesses' credit reports with flood depths from Harvey in difference-in-differences estimations. Flooded firms fell behind on their debt obligations, though these businesses avoided the most serious credit outcomes such as bankruptcy. Only independent businesses show signs of distress; subsidiaries of larger firms do not. Second, how did firms finance losses from Harvey? Firms were largely uninsured for their losses and were often denied credit after Harvey. Many funded recovery through informal means, such as friends and family financing. Our study highlights and quantifies the challenges posed by financing frictions in the wake of a negative shock.

Keywords: Financing Frictions · Climate Risk · Corporate Risk Management

JEL Classifications: D22 · G32 · Q54

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1 Introduction

Financially constrained firms, such as small businesses, may struggle to efficiently manage negative shocks. Financing frictions can crowd out *ex ante* risk management, as purchasing insurance and holding reserves compete with more immediate needs of cash-strapped firms (Rampini and Viswanathan, 2010). Frictions also limit access to *ex post* financing such as credit (Froot et al., 1993). Without effective risk management, constrained firms who experience a shock may turn to costly recovery strategies or even fall into financial distress. The extent of financial distress and the financing strategies affected firms use to navigate recovery are not well understood.

While a large literature shows that financing constraints inhibit entrepreneurship and growth (see Heil, 2018, for a review), the literature is more limited on how constrained firms cope with negative shocks. Empirical studies face two main challenges. First, adverse events are frequently endogenous to firm fundamentals or market conditions (e.g., asset bubbles), making shocks and financial distress difficult to disentangle. Second, frictions are thought to be greatest among small private firms, and data on privately-held U.S. firms are scant. The most accessible data – corporate filings, banks' call reports, and aggregated measures of economic output – offer limited visibility into the finances of individual private firms.

Our setting and data overcome these two limitations. First, we focus on the effects of Hurricane Harvey, which represents a large, exogenously-timed negative shock. We compare a random sample of small, independent firms from the area affected by the storm (Southeast Texas) to a control group of similar firms from throughout the U.S. We match businesses using their full street address with highly granular data on flooding from Harvey. Second, we analyze the credit reports of our sample firms, which provide detailed information on credit balances, inquiries, and loan repayment behavior. The credit data begin in June 2017 (two months prior to Harvey) and end in June 2018 (ten months post-Harvey). This approach allows us to evaluate the causal effects of Harvey-related flooding on credit outcomes against a counterfactual in which Harvey did not occur. To complement these data, we surveyed businesses in Southeast Texas roughly one year after the storm, asking about their losses and how they financed recovery. We conducted this survey because risk management data is central to understanding how firms cope with shocks.

The literature offers mixed predictions regarding whether localized, negative shocks would cause firms to fall into financial distress. In a frictionless world, they would not: affected firms would manage these shocks by issuing debt or equity if their cash flows were insufficient to meet their financial obligations. Yet frictions may pervade the operations of small firms. *Ex post* financing constraints – a firm's limited access to debt and equity financing after a shock – typically have been viewed as a motivation for firms to manage risk through insurance and reserves, reducing the risk of financial distress (Froot et al., 1993). However, recent research indicates that *ex ante* financing constraints can inhibit risk management – by dedicating their limited financing to production and expansion, firms allocate fewer resources to insurance and building reserves (Rampini and Viswanathan, 2010). Similarly, available borrowing capacity can help firms manage negative shocks, but maintaining such financial flexibility tends to be a challenge for constrained firms (Giroud and Mueller, 2017). Frictions may thus limit the protections with which a firm enters a shock, its access to financing during recovery, or both. Our results are organized around two questions, each of which offers insight into how firms responded to a large negative shock.

To what extent did Harvey cause firms financial distress? We measure financial distress using credit impairments in our credit report data. Impairments are a consequential outcome – they signal a firm's inability to meet its contractual obligations and so may increase borrowing costs, limit future access to credit, and affect other agreements (e.g., supply chain partnerships, leases). In our analysis, we examine the relationship between flood depth and credit impairment in treatment-intensity, difference-in-differences regressions.

We find a significant increase in delinquencies among firms flooded during Harvey. On average, Harvey caused a 9.5 percentage point increase in delinquent loan balances for firms in the most flooded areas. This represents an 86% increase in impaired balances relative to pre-Harvey levels. We observe this effect only for short-term delinquencies (< 90 days); we do not find a significant effect on the most serious credit outcomes, such as bankruptcies. Delinquencies also significantly increased among local firms whose properties were *not* flooded, suggesting spillover effects from flooded areas that meaningfully affected the cash flows of these firms.

Firms with fewer financing barriers may be less susceptible to financial distress. We replicate our loan impairment analyses (which use a sample of independent businesses) using a sample of businesses that are subsidiaries of a parent company. Our rationale for this analysis is that businesses with parents may have access to additional resources (e.g., via internal capital markets, Campello, 2002; Desai et al., 2008; Giroud and Mueller, 2019). These businesses have distinct credit reports from their parent companies. In contrast to our main results, we find that businesses with parents do *not* become delinquent on their loans, suggesting that commensurate levels of flooding caused them less financial distress.

Our survey data also reveal specific losses caused by Harvey and the financial challenges that ensued. Harvey caused property damage to 39% of respondents, and nearly 90% lost revenue because of the storm. Firms experienced utility outages, employee disruptions, reduced customer demand, and more. More than a quarter of firms who were profitable pre-Harvey were no longer profitable a year later. Many negatively affected firms struggled with recovery – 45% still had not fully recovered a year later, 3% said they would never fully recover, and 4% had closed permanently.

How did firms finance losses from Harvey? Having examined the magnitude of financial distress Harvey caused for local firms, we now consider their recovery financing strategies, which speak to their constraints and financial health. Using the credit report data, we analyze firms based on their *ex ante* borrowing. Firms *without* existing debt when Harvey occurred may have preserved their financial flexibility in the form of untapped capacity to borrow. Indeed, we find that firms *without* existing balances were more likely to take on debt because of the storm – balances increase in flood depth for these firms. More leveraged firms may be limited in their ability or willingness to finance recovery with debt. We find that firms *with* existing debt tended to reduce their overall debt levels. In the most heavily flooded areas, the loan balances of firms with existing debt fell by 50%. These firms appear credit constrained, as they applied for new credit while their debt balances were declining.[1]

[1] In addition to lender-driven credit supply constraints, some reduction in debt balances may be demand-driven: firms may voluntarily deleverage due, for example, to cash flow disruptions caused by Harvey.

Our survey offers insights into a broad set of recovery financing strategies employed by firms, including credit use. Similar to the credit report results, we find that Harvey increased credit demand but also revealed firms' binding credit constraints: 48% of affected firms applied for new credit post-Harvey, and more than half of those applicants were denied.[2] Overall, about a quarter of respondents ultimately used credit to finance recovery. *Half* of surveyed firms used informal financing from friends and family to recover. Firms typically avoid informal financing as it can have long-term consequences, leading them to take on less risky projects with lower returns (Lee and Persson, 2016). Thus, firms' reliance on friends and family financing following Harvey suggests constrained access to arms-length financing (insurance, credit, etc.). Consistent with this interpretation, we also find that insurance played a small role in firms' recovery – only 15% of surveyed firms used insurance to finance losses from Harvey.

In summary, our findings appear to align with the the literature's predictions regarding risk management and constraints. With respect to *ex ante* financing frictions, we find that firms rarely financed losses with insurance (e.g., Rampini and Viswanathan, 2010). Regarding *ex post* financing frictions, we find that businesses often faced financing barriers following the shock (e.g., Froot et al., 1993; Giroud and Mueller, 2017). Frictions limit firms' access to low-cost financing, implicitly pushing firms into higher-cost strategies when recovering from a shock. Consistent with this expectation, we find that affected firms frequently employ recovery strategies that likely reduce their long-term profitability such as neglecting debt payments and turning to informal financing. Firms with fewer constraints – namely, those with available credit limits and those with parents – appear better able to navigate an unexpected negative shock.

Our study contributes to the literature in several ways. We provide new insights by tracing out the effects of a large, negative shock on the financial health of privately-held firms. While a notable literature examines how shocks affect publicly-traded firms (e.g., Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Giannetti and Yu, 2021; Hsu et al., 2018; Huynh and Xia, 2021), research on private firms is more limited. Several recent studies examine how events such as the

[2] We asked firms about private loans as well as Small Business Administration disaster recovery loans. Disaster recovery loans are the only form of federal assistance offered to firms, and those loans are not reported to credit agencies. Fewer than five percent of surveyed firms used disaster recovery loans, indicating that in the aggregate, federal assistance to firms played a small role in financing their recovery.

COVID-19 pandemic (e.g., Bartlett and Morse, 2021; Fairlie, 2020; Kim et al., 2020) and economic downturns (e.g., Berger et al., 2017; Chodorow-Reich, 2013) affect small and medium businesses. We complement that literature by using novel, detailed firm data to study a shock that destroys physical capital and disrupts production. We find that even heavily flooded firms avoided defaulting on their credit obligations – delinquencies remained at 90 days or less one year after Harvey. This pattern may reflect businesses' substantial efforts to fulfill their debts. The steps they took to avoid default, such as using informal financing, may affect business operations in the future. A blockbuster catastrophe such as Harvey would be expected to create some challenges for local firms. Our focus is on the *extent* of financial distress for local firms as the extent is unclear and, in large part, may depend on a firm's risk management.

Our findings additionally contribute to research on financing frictions and their consequences (e.g., Campello et al., 2010; Gilje and Taillard, 2016; Gilje et al., 2020; Giroud and Mueller, 2017; Lee and Persson, 2016; Rampini and Viswanathan, 2010). We add to this literature by examining firms in the aftermath of a severe adverse event where financing constraints are likely to bind. We find evidence of constraints for small businesses, both *ex ante* (insufficient insurance) and *ex post* (credit rationing, reliance on friends and family financing). These constraints seem to contribute to their distress following the shock. For example, flooding caused independent businesses to fall behind on their debts, but flooding did not significantly affect businesses with parents.

We also contribute to a growing literature on how severe weather and climate risks affect firms and financial markets (e.g., Bernstein et al., 2019; Brown et al., 2021; Collier et al., 2020; Cortés and Strahan, 2017; Giroud et al., 2012; Ouazad and Kahn, 2021). For example, Brown et al. (2021) show that firms manage cash flow shocks created by severe winter weather by drawing on credit lines. Basker and Miranda (2018) examine firms' post-Katrina survival, productivity, and employment using Census Bureau data and find that survival is less likely for smaller firms and for firms reporting more limited access to credit. This literature on climate risk speaks to an important and growing form of business uncertainty, and we offer a unique contribution to it by analyzing a combination of third-party credit reports and self-reported survey data to trace out the effects of a severe climate event.[3]

Our paper is structured as follows. We provide background on Hurricane Harvey in the next section. In Section 3, we describe and analyze the credit report data. Our survey analysis and results are in Section 4. In Section 5, we summarize our findings and discuss their implications.

2 Background

On August 26, 2017, Hurricane Harvey made landfall near Rockport, Texas as a Category 4 tropical cyclone. Harvey stalled over the Houston metro area, dropping more than 27 trillion gallons of rain.[4] Resulting flood waters covered more than a quarter of the Houston metro area. Nederland, Texas received over 60 inches of rain during Harvey, setting a new U.S. record for rainfall from a single event. Flood waters damaged more than 300,000 structures and as many as 500,000 cars. Harvey caused an estimated $125 billion in damages, making it the second-costliest U.S. tropical cyclone after Hurricane Katrina. Frame et al. (2020) estimate that climate change increased economic losses from Harvey by at least one-third.

In addition to direct physical damage, the storm also disrupted access to utilities and public infrastructure. More than 330,000 entities lost electricity due to Harvey-related flooding. Cable internet service was interrupted for more than 280,000 customers in the immediate aftermath, and continued to affect more than 150,000 customers a week later (FCC, 2017). U.S. Mail service was suspended in many locations from August 25 to September 11 (USPS, 2017). At least 500 roads were closed due to flooding and damage, and 118 were still closed after two weeks (NPR, 2017).

Major Disaster Declaration DR-4332-TX designated 41 counties to receive federal aid (FEMA, 2017b). We refer to these counties as the "disaster area" throughout this paper. The only form of federal assistance offered to businesses is disaster recovery loans from the Small Business Adminis-

[3]At least two papers examine *households'* credit reports following hurricanes. Gallagher and Hartley (2017) and Billings et al. (2019) respectively examine how Hurricane Katrina and Hurricane Harvey affected households' finances.

[4]Statistics throughout this section are from Blake and Zelinsky (2018) unless otherwise cited.

tration (SBA). Small businesses can borrow up to $2 million from this program to repair damaged property and/or offset revenue losses. One year following Hurricane Harvey, the overall approval rate for SBA disaster loans was about 40% (GAO, 2020).[5]

3 Credit Report Analysis

3.1 Data and Summary Statistics

We analyze data from Experian credit reports. To construct the sample, we randomly drew 10,200 firms that were listed as active businesses in the *ReferenceUSA* database in 2016. This includes a sample of 8,000 firms in 49 Texas counties – 26 counties in the disaster area and 23 counties outside of the disaster area.[6] We stratified these 8,000 firms by county based on the number of firms reported for each county in the U.S. Census Bureau County Business Patterns (U.S. Census Bureau, 2017b). The other 2,200 firms are a random sample from across the U.S., similarly stratified by state based on the number of businesses in each state. We observe each firm's credit reports on June 30, 2017 and again on June 30, 2018. While most credit outcomes are reported at the two dates only, some variables provide more time-granular information, reporting outcomes in months or quarters. We use both structures of credit outcomes for our analysis.

Table 1 outlines our data filtering steps. First, the business must have a credit report in June 2017. Second, we keep a single credit record for each business, omitting duplicates. Experian provides credit reports at the business level, so all establishments within a business have the same credit report. In most cases, duplicates appear to be local branches of a large business. Third, we exclude businesses listed by Experian as having 500 or more employees based on the common standard that "small businesses" have fewer than 500 employees (e.g., SBA, 2014). Fourth, we omit businesses that have a parent according to *ReferenceUSA*. We focus our analyses on businesses with

[5]Federal aid also includes funds to local governments for debris removal and repair of public property and infrastructure. Affected households can apply for federal grants and low-interest loans. The average grant amount was $8,900 (capped at $34,000); a fifth of households who applied for a grant received one (Walls and Cortes, 2018).

[6]According to the County Business Patterns of the U.S. Census Bureau (2017b), 95% of businesses within the disaster area were located in these 26 counties. Hurricane Harvey primarily affected two SBA administrative districts in Texas, the Houston District and the Lower Rio Grande Valley District. We coordinated with these SBA district offices in disseminating the survey in Section 4. Our Texas random sample of credit reports uses counties in those districts to facilitate comparisons between the credit report and survey analyses.

fewer than 500 employees and without parents out of concern that larger, multi-business firms may have access to additional resources (e.g., internal capital markets) that make these firms distinct from the other businesses in our sample. These filters reduce the data for our credit report analysis to the "Full Sample" of 8,219 firms.

In our sample for analysis of impairments, a firm must have positive loan balances on both June 30, 2017 and June 30, 2018. We restrict the sample in this way as only firms that are actively borrowing can have loan impairments. This filter creates a smaller "Active Borrower Sample" of 2,614 firms. The loans we observe in the Experian credit report data are those that have had at least one update in the past three months; our "Active Borrower Sample" thus ensures that we capture the most current changes in a firm's ongoing credit performance.[7]

Table 1: Data Cleaning and Filtering: Main Samples

Data Step	**Remaining Firms**
All firms with Experian credit records	10,200
Drop if no 2017 credit record	9,990
Drop duplicate credit records	9,722
Drop if number of employees $\geq$ 500	9,392
Drop if has a parent (according to *ReferenceUSA*)	8,219
Full Sample	**8,219**
Drop if 2017/2018 total loan balances = $0	2,614
Active Borrower Sample	**2,614**

Credit Variables. Our primary outcome of interest in the credit report data is loan impairment, which we measure in several ways. First, we consider the proportion of total loan balances in four delinquency categories: 1-30 days delinquent, 31-60 days, 61-90 days, and over 90 days ("PctDelinquent, X days"). We then create a new variable ("PctImpaired") indicating the share of total loan balances that are not paid on time within the agreed terms, defined as:

$$\begin{aligned}\text{PctImpaired}_{it} = {} & (\text{PctDelinquent, 1-30 days})_{it} + (\text{PctDelinquent, 31-60 days})_{it} \\ & + (\text{PctDelinquent, 61-90 days})_{it} + (\text{PctDelinquent, over 90 days})_{it}. \end{aligned} \tag{1}$$

[7] As a robustness check for the analyses of impairments, we also examine samples including firms with zero balances in 2017 or/and 2018, setting impairments as zeros for these periods.

To evaluate more severe impairments, we examine the amount placed in collections in the last seven years, and the liability amount of legal filings (i.e., tax liens, judgments, and bankruptcies) in the last seven years.

To examine how Harvey affected credit use, we study a firm's total loan balances and number of new credit inquires. Other credit report variables that we use as controls include the number of employees and the number of years the firm has appeared in Experian's files.

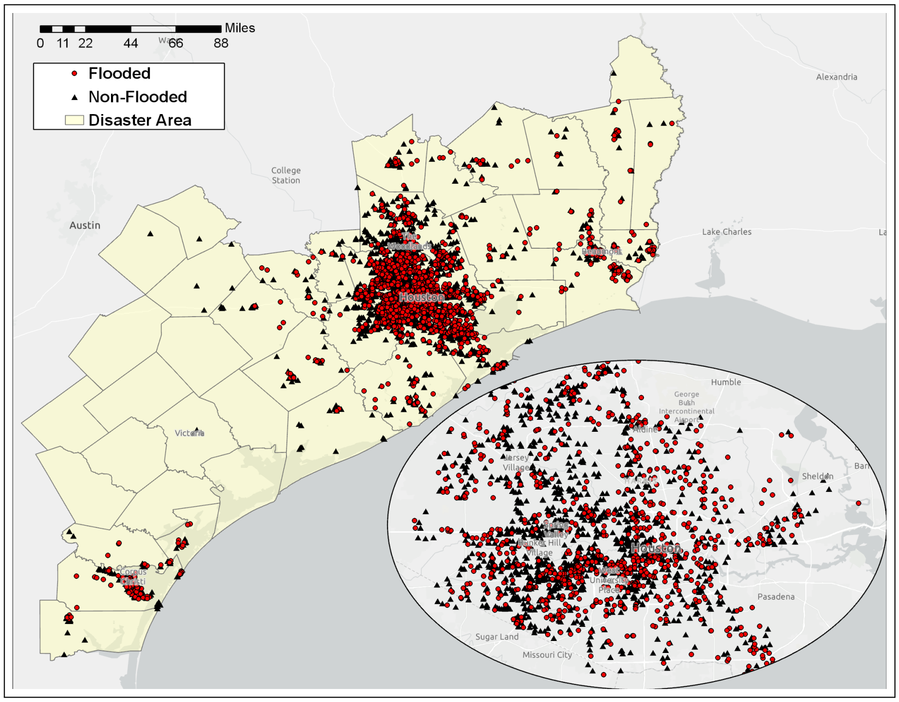
Flood Variables. We use flood depth at the firm's location as our treatment variable. We geocode the primary business address of the firm as of June 2017 and match the coordinates to FEMA's estimated Harvey-related flood depth at that address ("Flood Depth"; FEMA, 2018). This measure of flooding uses water levels observed at river gauges and high water mark lines to interpolate flood depth throughout the disaster area. The estimated flood depths are continuous in feet, measuring up to 100 feet. Figure 1 presents the flooding distribution (flooded vs. non-flooded) of firms in the disaster area from our random sample, based on the FEMA flood depth data. About 39% of the firms located in this area are identified as flooded (red circles) and they are widespread across the disaster counties. For our primary analyses, we group flooded firms into terciles based on the flood depth at their location. The first tercile includes firms in areas with less than 1.7 feet of flooding. The third tercile includes firms in areas flooded 2.7 feet or more.[8] We also investigate effects using two other specifications: logged flood depth and an indicator for any flood depth.

As a robustness check, we employ a second measure of flooding, "Remote Sensing" (FEMA, 2017a). This measure is binary (flooded vs. non-flooded) and uses Synthetic Aperture RADAR and Multispectral Imagery sensors to detect whether a particular location was flooded during Hurricane Harvey between August 26 and September 5, 2017.

Additional Control Variables. Using each firm's exact street address, we also identify its pre-Harvey flood risk zone designation using the FEMA National Flood Hazard Layer as of May 2017 (University of Texas, 2017). Flood risk zones comprise three broad categories, areas with: less than

[8] As a reference for the extent of damages caused by these levels of flooding, the U.S. Army Corps of Engineers reports that *homes* with a flood depth of 1.7 feet were about 30 percent damaged from Harvey and those with a flood depth of 2.7 feet were about 38 percent damaged (Houston Chronicle, 2018).

Figure 1: Studied Firms in Disaster Area: Flooded vs. Non-Flooded



a 1% annual flood probability, a 1% or greater annual flood probability, or a 1% or greater annual flood probability and vulnerable to storm-induced wave damage. Further, we merge our data with the U.S. Census Bureau's American Community Survey (ACS, 2016), which provides demographic information by ZIP code (e.g., mean income, population, education, race).

Summary Statistics. Table 2 provides summary statistics for our credit report data (measures are from the June 2017 credit reports). The first column describes the sample in total and is the focus of our description here; the remaining columns describe our control and treatment groups, which we discuss further in the sections below. The upper panel, marked "Full Sample," summarizes demographics, balances, and inquiries for our sample of 8,219 firms. Among these firms, the mean and median number of employees are 9.5 and 3.0, respectively.[9] On average, these firms had 16 years of credit history in 2017. Their average loan balances totaled $25,669 with a median value

[9]The distribution of firms by size in our sample is very similar to the national distribution. For example, 62% of firms in our sample have fewer than 5 employees (versus 62% in the County Business Patterns Data) and 91% have fewer than 20 employees (versus 89%, U.S. Census Bureau, 2017a).

of \$0 – over 60% of the full sample had no loan balances before Harvey. Their average number of credit inquires in the second quarter of 2017 was 0.14. That is, for every seven firms in our full sample, we observe one credit inquiry made by a firm in the quarter.

The lower panel of Table 2 summarizes credit for the active borrower sample of 2,614 firms. These firms had average loan balances of \$77,890, with 15% of loan balances not paid on time before Harvey. Of the total balances, 7% were 1-30 days delinquent, 2% were 31-60 days delinquent, 1% were 61-90 days delinquent, and 5% were over 90 days delinquent. Also, the average amount placed in collections was \$1,555 and the average liability amount of legal filings (i.e., tax liens, judgments, and bankruptcies) was \$12,002. Overall, a relatively small proportion of these firms had any type of delinquencies, collections, or legal filings. For example, only 14% had delinquencies over 90 days and only 10% had any records of collections or legal filings before Harvey.

3.2 Empirical Methodology

To examine how flooding from Hurricane Harvey affected firms' credit outcomes, we use difference-in-differences estimations in which flooding is the measure of treatment. The general model is

$$y_{it} = \alpha_0 + \alpha_1 \mathrm{I}_t(\text{Post-Harvey}) + \alpha_2 \mathrm{I}_i(\text{Flooded}) + \alpha_3 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Flooded}) + \varepsilon_{it} \qquad (2)$$

where i indexes firms and t indexes time, y_{it} is a general term for the credit outcome of interest, I_t(Post-Harvey) is an indicator for post-Harvey periods, and I_i(Flooded) is an indicator for firms that were flooded by Harvey. The coefficient α_3 captures the treatment effect.[10]

[10] The model estimates the intent-to-treat (ITT) effect, rather than the average treatment effect on the treated, due to imprecision in measuring flooding. Billings et al. (2019) use Harvey flooding to estimate ITT effects on households' credit outcomes. We can more precisely estimate flooding as we measure flooding at the exact address, while they measure flooding at the census block level. However, our flood measure is still subject to measurement error because flood levels are modeled, firms may not be located at ground level, etc. This measurement error will partially attenuate our estimates relative to true average treatment effects.

Table 2: Summary Statistics

Variable	Total	Outside	No Flood, Disaster Area	Flooding: 1st Tercile (1, 1.69 ft]	Flooding: 2nd Tercile (1.69, 2.68 ft]	Flooding: 3rd Tercile >2.68 ft
Full Sample						
No. of Firms	8,219	3,051	3,171	717	608	672
Employees	9.52	10.06	9.14	8.50	9.96	9.51
	[3]	[3]	[3]	[3]	[3]	[3]
	(27.71)	(30.69)	(24.32)	(28.36)	(28.63)	(26.92)
Years in File	16.02	16.48	15.67	15.49	16.81	15.38
	[14]	[15]	[14]	[14]	[15]	[14]
	(10.64)	(10.84)	(10.52)	(10.52)	(10.73)	(10.23)
Total Balance ($)	25,669	32,726	25,070	7,617	27,849	13,739
	[0]	[0]	[0]	[0]	[0]	[0]
	(349,843)	(500,607)	(232,620)	(44,564)	(294,560)	(151,200)
No. of Inquiries, Q2 2017	0.14	0.15	0.14	0.12	0.13	0.09
	[0]	[0]	[0]	[0]	[0]	[0]
	(0.65)	(0.71)	(0.66)	(0.42)	(0.59)	(0.46)
Active Borrower Sample						
No. of Firms	2,614	980	1,007	209	209	209
Employees	16.44	17.52	15.53	14.38	18.92	15.31
	[5]	[5]	[5]	[5]	[5]	[4]
	(42.15)	(46.45)	(37.25)	(42.85)	(46.29)	(38.02)
Total Balance ($)	77,890	100,814	74,683	25,959	72,967	42,706
	[1,700]	[2,100]	[1,800]	[1,600]	[1,100]	[1,700]
	(615,050)	(879,615)	(403,303)	(79,739)	(488,401)	(269,138)
PctImpaired	0.15	0.17	0.14	0.14	0.12	0.11
	[0]	[0]	[0]	[0]	[0]	[0]
	(0.28)	(0.3)	(0.28)	(0.27)	(0.25)	(0.26)
PctDelinquent, 1-30 days	0.07	0.07	0.08	0.07	0.06	0.04
	[0]	[0]	[0]	[0]	[0]	[0]
	(0.18)	(0.18)	(0.19)	(0.19)	(0.16)	(0.13)
PctDelinquent, 31-60 days	0.02	0.02	0.02	0.02	0.01	0.01
	[0]	[0]	[0]	[0]	[0]	[0]
	(0.09)	(0.1)	(0.09)	(0.08)	(0.03)	(0.07)
PctDelinquent, 61-90 days	0.01	0.02	0.01	0.01	0.01	0.01
	[0]	[0]	[0]	[0]	[0]	[0]
	(0.08)	(0.09)	(0.07)	(0.1)	(0.04)	(0.04)
PctDelinquent, over 90 days	0.05	0.05	0.04	0.04	0.04	0.05
	[0]	[0]	[0]	[0]	[0]	[0]
	(0.18)	(0.2)	(0.16)	(0.16)	(0.18)	(0.2)
Collection ($)	1,555	3,194	516	887	492	603
	[0]	[0]	[0]	[0]	[0]	[0]
	(25,954)	(41,883)	(4,783)	(5,803)	(4,262)	(4,776)
Legal Filing ($)	12,002	18,925	7,930	11,752	7,603	3,800
	[0]	[0]	[0]	[0]	[0]	[0]
	(145,895)	(215,557)	(92,442)	(64,735)	(48,610)	(20,506)

Notes: The values in the first, second, and third rows under each variable are means, [medians], and (standard deviations), respectively. All variables are from the firm's credit report on June 30, 2017.

We implement two versions of this general model. The first is a difference-in-differences model which imposes treatments at increasing flood depths. Specifically, we estimate

$$
\begin{aligned}
y_{it} = \beta_0 &+ \beta_1 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{No Flood, Disaster Area}) \\
&+ \beta_2 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Flood 1st Tercile}) \\
&+ \beta_3 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Flood 2nd Tercile}) \\
&+ \beta_4 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Flood 3rd Tercile}) \\
&+ \theta \mathrm{I}_t(\text{Post-Harvey}) \times X_i + \mathrm{FE}_i + \mathrm{FE}_t + \varepsilon_{it}.
\end{aligned} \tag{3}
$$

We use a set of indicators for whether a firm was located in one of five groups at the time of Hurricane Harvey: (1) outside the disaster area (the omitted reference group); (2) in the disaster area but not flooded ("I(No Flood, Disaster Area)"); (3) in the lowest flood depth tercile ("I(Flood 1st Tercile)"); (4) in the middle flood depth tercile ("I(Flood 2nd Tercile)"); (5) in the highest flood depth tercile ("I(Flood 3rd Tercile)"). We consider firms in the disaster area that were not flooded as "treated" because of possible spillovers from the disaster, e.g., due to changes in consumer demand, utility outages, employee disruptions, etc. The treatment effects in Eq. (3) are captured by β_1 to β_4.

We interact a set of pre-Harvey control variables X_i with the post-Harvey indicator as a way of controlling for non-flood heterogeneity in Harvey's effects. The control variables include the firm's number of employees, the years that a firm had a credit file (a proxy for firm age), an indicator for industry (based on 2-digit SIC code), its ZIP-level demographic information (logged mean income, logged population, the proportion white, proportion with bachelor's degrees, and the Gini coefficient for income). We also control for the flood risk zone of firms in the disaster area. Models include firm fixed effects (FE_i) and time fixed effects (FE_t). We also investigate several alternative specifications of flooding (e.g., logged flood depth).

For several credit outcomes, the credit reports provide more time-granular information (e.g., monthly loan balances). To examine how these credit outcomes evolve over time, we implement an event study version of Eq. (2), which replaces I_t(Post-Harvey) with a set of indicators I_t(Time) for each time period, expressed as

$$y_{it} = \gamma_0 + \sum_t \gamma_{1t} \mathrm{I}_t(\text{Time}) \times \ln(\text{Flood Depth}_i) + \sum_t \theta_t \mathrm{I}_t(\text{Time}) \times X_i + \mathrm{FE}_i + \mathrm{FE}_t + \varepsilon_{it}. \tag{4}$$

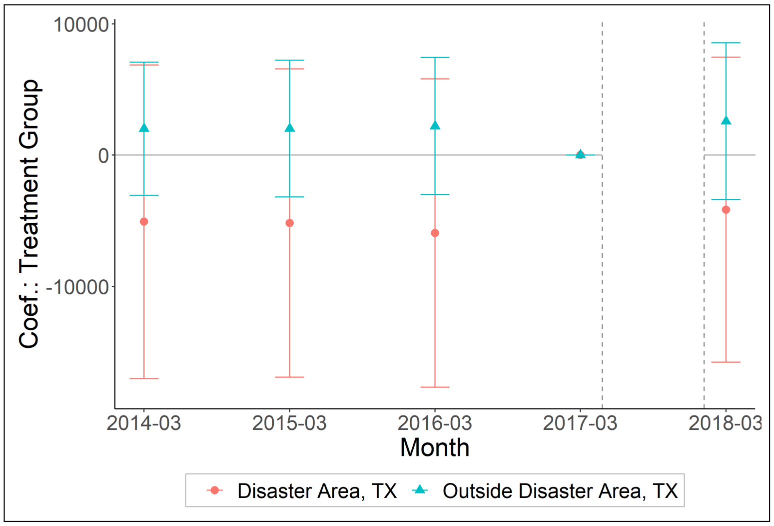
The last observation before Harvey, in June 2017, serves as the reference period. We use logged flood depth (instead of flood tercile indicators) in these estimations to make the event study figures easier to interpret.

The regressions in Eq. (3) and (4) estimate a causal effect of flooding on the studied credit outcomes (e.g., delinquency) under two assumptions. First, given model controls, treatment assignment can be viewed as random with respect to the considered credit outcomes. Regarding this assumption, the timing and severity of flooding can be understood as quasi-random in the disaster area: flooding notably differs across hurricanes that affect the same area due to variation in rainfall intensity and location. Since we control for FEMA flood risk zones, results can be interpreted as comparisons within a flood zone.

The second identifying assumption is that the control and treatment groups would respond comparably had they both been affected in the same way by Harvey, commonly called the "parallel trends" assumption. We examine pre-event trends in our outcomes of interest at the firm level (e.g., loan balances and inquiries) for the treatment and control groups using the event study model from Eq. (4). This analysis provides general support for the parallel trends assumption as none of the pre-Harvey coefficients are significantly different from zero (Figure B.1.2 of the Appendix). Additionally, we examine aggregate business statistics at the county level (e.g., establishment count, firm entry, firm exit, etc.) and implement difference-in-differences estimations, in which counties outside Texas are the control group and counties in Texas are the treatment group. We show in Figure 2 that pre-event trends for the number of establishments in counties in the Harvey disaster area and other counties in Texas do not statistically differ from the national trend (see Table B.1.1 for additional outcomes).

There are two additional considerations when interpreting our results. The first is how potential firm exits (i.e., permanent closures) due to Harvey may affect our estimates. Our measurement of loan impairments should be unaffected, as credit reports accurately describe impairments even if a

Figure 2: Number of Establishments at County Level



Note: The reference group is counties outside of Texas. The dotted vertical lines mark the time when Harvey occurred. Data are from Business Dynamics Statistics and Nonemployer Statistics of the U.S. Census Bureau (2018a,b). The data include sole proprietors with no paid employees and establishments of firms with fewer than 500 employees.

firm closes permanently. However, our estimates of credit demand, based on inquiries and balances, could be affected by firm closures and so should be understood as lower-bound estimates.[11] The second consideration is how our results generalize to other severe climate events. For reference, we also examine aggregate business statistics for two other large urban hurricanes, Hurricane Sandy and Hurricane Katrina in Appendix B.1. The one-year post-hurricane trends in affected counties appear largely similar to Harvey – we do not observe significant changes in county-level business statistics, such as the number of establishments, the firm exit rate, total employment, etc. (see Table B.1.2 and Table B.1.3). These comparisons do not guarantee generalizability, but do align with previous findings indicating that Harvey appears similar to other large-scale hurricanes (e.g., Billings et al., 2020).

[11] Lenders maintain credit records for several years after a firm closes. For example, consider a firm who closes with unpaid loans. The lenders to that firm will continue to report as those loans becomes more and more delinquent over time. Severe impairments such as legal filings remain on the firm's report for seven years, but the credit report does not indicate whether a firm has permanently closed. In addition to impairments, we examine firms' inquiries and balances after Harvey. Closed firms would not apply for new credit, so by inadvertently including closed firms, our analyses could underestimate credit demand.

3.3 Results

This section describes the effects of flooding on three credit outcomes: impairments, inquiries, and balances. In the first two subsections, we examine overall impairments (Section 3.3.1) and further decompose impairment by length of delinquency (Section 3.3.2). We also examine the impairments of businesses *with* parents and compare the results to our main sample (comprised of businesses without parents) in Section 3.3.3. In Section 3.3.4, we discuss our event study results using more time-granular data on inquiries and balances, with additional focus on heterogeneity across firms.

3.3.1 Impairment

We evaluate whether Harvey caused firms to delay paying their loans by examining the share of loan balances that are not paid within the agreed time period ("PctImpaired"). Table 3 presents the results of estimating Eq. (3) for the active borrower sample defined in Section 3.1.[12] In the table from Columns (1) to (5), we include our flood tercile variables and an indicator variable ("I(No Flood, Disaster Area)") which captures businesses who were not flooded according to FEMA estimates but were located in a disaster-affected county. Our reference group is firms that are located outside of the area affected by Harvey. We begin with a parsimonious specification (without any controls) in Column (1) and add fixed effects and controls step-wise across the columns. Our preferred model is Column (5), which includes firm controls (age, size, industry, and flood zone designation), ZIP code controls (mean income, population, etc.), and firm and year fixed effects. We also include an indicator for firms located in Texas to control for potential systemic differences between these firms and those in other states.

Column (5) shows that flooding is positively and significantly related to the change in a firm's impaired loan balances, and that the magnitude of the effect is largest for the most severely flooded firms. On average, for firms in the highest flood tercile, Harvey caused a 9.5% share of their

[12]The active borrower sample includes only firms who had positive balances in *both* 2017 and 2018, which provides a balanced panel. These active borrowers are the population of interest for assessing loan impairments because, mechanically, firms without loan balances cannot be be delinquent. As robustness tests, we conduct the same analysis and (1) include the 478 firms who had positive 2017 total balances but zero 2018 total balances, and (2) use the full sample, which includes firms with zero balances in 2017. In both cases, the results are similar to those presented in Table 3, although as one might expect, the coefficients are smaller in the full-sample estimation (see Appendix Table B.1.4).

Table 3: Share of Balances that are Impaired, Active Borrower Sample

	PctImpaired							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Post-Harvey) ×								
I(No Flood, Disaster Area)	0.028***	0.031***	0.028***	0.022*	0.034**	0.034**	0.016	0.046***
	(0.010)	(0.010)	(0.010)	(0.012)	(0.016)	(0.016)	(0.015)	(0.015)
I(Flood 1st Tercile)	0.054***	0.065***	0.054***	0.049***	0.061***			
	(0.016)	(0.015)	(0.016)	(0.016)	(0.019)			
I(Flood 2nd Tercile)	0.058***	0.0458**	0.058***	0.050***	0.062***			
	(0.012)	(0.018)	(0.012)	(0.014)	(0.017)			
I(Flood 3rd Tercile)	0.091***	0.078***	0.091***	0.083***	0.095***			
	(0.016)	(0.017)	(0.016)	(0.016)	(0.019)			
I(Flooded)						0.072***		
						(0.016)		
ln(Flood Depth)							0.056***	
							(0.013)	
I(Flooded, Remote)								0.072***
								(0.019)
I(TX)					−0.018	−0.018	−0.017	−0.019
					(0.016)	(0.016)	(0.015)	(0.016)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP FE	No	Yes	No	No	No	No	No	No
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	2,614	2,614	2,614	2,614	2,614	2,614	2,614	2,614
Firm-Year Obs	5,228	5,228	5,228	5,228	5,228	5,228	5,228	5,228
R^2	0.004	0.339	0.792	0.793	0.793	0.792	0.793	0.792

Note: Dependent variable is the share of loan balances that are not paid on time within the agreed terms for a firm's continuously reported loans ($PctImpaired_i$). Our preferred model is in Column 5, in which we also include an indicator for firms located in Texas to control for any potential systemic differences between these firms and those in other states. Disaster area represents being in one of the 41 counties that were eligible for federal aid in the presidential disaster declaration DR-4332-TX. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

total balances to become impaired 10 months after the disaster. Before Harvey, 11% of their loan balances were impaired on average (see the rightmost column of Table 2), so this effect represents an 86% increase over the pre-Harvey level for these firms. The estimated regression coefficient provides the average effect within the third tercile; however, there is substantial heterogeneity in impairment among firms in the most flooded area. About one-third of these firms had any increase in impairment, and approximately 9% of the firms had over half of their loan balances become impaired.[13]

Firms in the disaster area that did not experience flooding at their location had a 3.4% share of their total balances move into impairment. This increase in impairment among non-flooded firms might indicate spillover effects from flooded areas (e.g., firms may have been unable to repay their lenders because of lost revenue from customer disruptions) or that the firm incurred damage at another location (e.g., damage to automobiles parked elsewhere).

The results are qualitatively similar throughout all specifications in Column (1) to Column (5). Inclusion of firm, industry, and ZIP code controls does not substantially change the estimated effects of flooding. Controlling for the flood zone of firms in the disaster area also does not change our results. That is to say, a firm's loan impairments depend on its actual flood experience in Harvey, irrespective of whether it was located in an area with a high risk designation on flood maps.

Similarly, we observe positive and significant effects using two alternative specifications of flooding based on our "Flood Depth" data: an indicator for whether the firm experienced any flooding ("I(Flooded)") in Column (6), and the logged continuous flood depth ("ln(Flood Depth)") in Column (7).[14] The results are also robust to using an alternative measure of flooding: Column (8) shows that impairment increased in flooded areas when using a flood indicator based on our remote sensing data ("I(Flooded, Remote)").[15]

[13]To provide further context, we examine changes in Experian's proprietary "Intelliscore" index of credit quality. The score ranges between 0 and 100, with lower scores indicating higher credit risk (Experian, 2013). For flooded firms with an increase in impairment, their average Intelliscore decreased from 50 to 35, about half of one standard deviation. Intelliscore groups businesses into one of five risk classes and half of these firms were downgraded by at least one risk class.

[14]When using logged flood depth, we recode the cases in which the flood depth is zero as ln(Flood Depth) = 0 and identify these firms with the regression dummy, "I(No Flood, Disaster Area)."

[15]We also examined whether severe wind increased loan impairments using catastrophe modeling data from AIR Worldwide. However, wind data are quite limited, available for only 7.6% of the sampled firms in Texas. We do not observe any significant effects on loan impairments due to wind; however, this null result may be due to the limitations of these wind data.

3.3.2 Decomposition of Impairment and Severe Outcomes

We decompose impairment into four categories by length of delinquency: 1-30 days delinquent, 31-60 days delinquent, 61-90 days delinquent, and over 90 days delinquent. Columns (1) to (4) in Table 4 present the regression results for delinquencies. The dependent variables are the share of a firm's outstanding loan balances that are delinquent ("PctDelinquent") in each of the four categories. The largest effect from flooding is on the shortest-term delinquencies (1-30 days delinquent): on average, being in the highest tercile of flood depth led firms to make payments that were 1 to 30 days late on a 5.8% share of their total loan balances. This more than doubles the share of their loan balances that were 1-30 days delinquent prior to Havey. We observe a smaller but also significant effect on 61-90 day delinquencies, these increased by a 2.2% share of their total balances for firms in the third flood depth tercile. This represents more than a 200% increase over their pre-Harvey levels. The longest delinquency level (over 90 days delinquent) does not appear to be significantly affected.

In this table, we also evaluate more severe credit outcomes: the amount placed in collections (Column 5) and the liability amount in legal filings (i.e., tax liens, judgments, and bankruptcies, Column 6). These two variables reflect the cumulative liability amount of any collections and legal filings in the previous seven years. We do not observe significant increases in these extreme credit outcomes for firms in the most flooded tercile.[16]

In Appendix B.1, we also look at the *number* of reported loans (versus the balances examined here), examining whether Harvey affected the share of loan contracts that are impaired. This provides insights on how impairments are distributed across different loans owed by the same firm. We find that the ratio of impaired loans, particularly those that are on average 1-30 days and 31-60 days delinquent, increases for flooded firms, although the magnitude of the effect does not seem to differ significantly by the levels of flooding (Table B.1.6).

[16] Although firms in the first flood tercile appear to have some significant increases in collections and firms in the second flood tercile had significant decreases in legal filings, these results are mainly driven by one or two observations.

Table 4: Share of Balances that are Delinquent, Collections, and Legal Filings

	PctDelinquent					
	(1) 1-30 days	(2) 31-60 days	(3) 61-90 days	(4) 90+ days	(5) ln(Collection)	(6) ln(Legal)
I(Post-Harvey) ×						
I(No Flood, Disaster Area)	0.010	0.003	0.011**	0.009	0.036	−0.055
	(0.011)	(0.006)	(0.005)	(0.010)	(0.056)	(0.039)
I(Flood 1st Tercile)	0.026*	0.017**	0.012**	0.007	0.189**	0.049
	(0.014)	(0.007)	(0.005)	(0.009)	(0.074)	(0.120)
I(Flood 2nd Tercile)	0.035**	0.014*	0.011*	0.002	−0.138	−0.145**
	(0.017)	(0.007)	(0.006)	(0.009)	(0.142)	(0.060)
I(Flood 3rd Tercile)	0.058***	0.008	0.022***	0.007	0.077	−0.151
	(0.014)	(0.008)	(0.005)	(0.011)	(0.123)	(0.096)
I(TX)	−0.017	0.00001	−0.005	0.003	0.095	−0.065
	(0.013)	(0.007)	(0.006)	(0.010)	(0.071)	(0.064)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	2,614	2,614	2,614	2,614	2,614	2,614
Firm-Year Obs	5,228	5,228	5,228	5,228	5,228	5,228
R^2	0.687	0.562	0.712	0.870	0.916	0.947

Note: Dependent variables from Columns 1 to 4 are the share of a firm's continuously reported loan balances that is delinquent ($PctDelinquent_i$) at four different levels: 1-30 days delinquent, 31-60 days delinquent, 61-90 days delinquent, and over 90 days delinquent. Dependent variable in Column 5 is the logged dollar amount placed in collections in the previous seven years ($ln(Collections_i)$). Dependent variable in Column 6 is the logged liability amount of legal filings (i.e., tax liens, judgments, and bankruptcies) in the last seven years ($ln(Legal_i)$). The models include firm fixed effects, year fixed effects, and control variables. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Taken together, the results show a meaningful decline in firms' loan performance due to Hurricane Harvey. We do not find that flooding affected the most severe credit outcomes, such as collections and legal filings. These outcomes are somewhat rare, so our analysis may have insufficient power to detect them (e.g., fewer than 3% of firms in the control group had an increase in collections or legal filings).

In addition, it could be that the worst credit outcomes do not occur until after the end of our credit data, which ends just under a year post-Harvey. One-year outcomes, however, are important benchmarks in the literature, including in prominent studies using consumers' credit reports (e.g., Finkelstein et al., 2012). Our findings motivate future research to examine credit outcomes over longer time horizons.

3.3.3 Impairment: Businesses with Parents

In this section, we investigate the effects of flooding on loan impairments for small businesses *with* parents. These businesses are subsidiaries in multi-business firms, according to *ReferenceUSA*, and have a distinct credit report from the parent company. Compared to businesses *without* parents, we expect that businesses with parents have additional resources that may reduce their financial distress and so improve their ability to meet their existing credit obligations following Harvey. For example, businesses with parents experience fewer financing frictions due to access to internal capital markets (e.g., Campello, 2002; Desai et al., 2008; Giroud and Mueller, 2019). While financing frictions are a well-documented distinction, subsidiaries may differ from independent businesses along several dimensions. It is important to note that our analyses here do not identify what features of businesses with parents may lead them to respond to Harvey differently.

Businesses with parents are excluded from the baseline sample that we use in the analyses above. The sample of businesses with parents includes 1,173 businesses, 313 of which are active borrowers. Compared to the baseline sample, these active borrowers are larger: the median business has 10 employees (versus 5 in the baseline sample, see Appendix Table B.1.7). The industry composition also differs: 18% of these active borrowers *with* parents are in finance, insurance, and real estate versus only 8% in the baseline sample.

We replicate our preferred difference-in-differences specification on overall impairments (reported in Table 3, Column (5)). Table 5 reports our results for the samples with parents. Column (1) is a replication using our baseline (non-parent) sample for reference. In Column (2), we report the estimation using the sample of active borrowers *with* parents. Because of the smaller sample size, we use below- and above-median flood depth as the measure of flooding instead of depth terciles. In contrast to firms *without* parents, we do not observe significant changes in the share of loan balances that are impaired for flooded firms *with* parents. These results suggest that businesses with parents are less likely to enter financial distress, as measured by loan impairment, for a given level of flooding.

Table 5: Share of Balances that are Impaired, Active Borrowers with vs. without Parents

	PctImpaired			
	(1)	(2)	(3)	(4)
I(Post-Harvey) ×				
I(No Flood, Disaster Area)	0.034**	−0.002	−0.025	−0.062***
	(0.016)	(0.044)	(0.042)	(0.022)
I(Flood ≤ Median)	0.055***	−0.004	−0.012	−0.005
	(0.016)	(0.062)	(0.045)	(0.032)
I(Flood > Median)	0.090***	−0.009	−0.033	−0.041
	(0.018)	(0.052)	(0.051)	(0.033)
I(TX)	−0.018	0.020	0.017	0.007
	(0.016)	(0.050)	(0.049)	(0.038)
Parents	No	Yes	Yes	Yes
Weighted	No	No	Propensity Score	Industry & EE size
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes
No. of Firms	2,614	313	313	313
Firm-Year Obs	5,228	626	626	626
R^2	0.793	0.755	0.738	0.760

Note: Dependent variable is the share of loan balances that are not paid on time within the agreed terms for a firm's continuously reported loans ($PctImpaired_i$). The sample in Column 1 is our baseline active borrower sample with no parents. The sample in Columns 2 to 4 consists of active borrowers with parents, among whom 54 firms were flooded. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

One potential concern is that the observed differences between Columns (1) and (2) might not be due to whether a business has a parent, but instead to compositional differences (e.g., industry, size) between businesses with and without parents. While our preferred specification in Column (2) of Table 5 controls for size and for features of the business with fixed effects, these controls might be insufficiently flexible. To address this, we estimate the model using a weighted approach (Imbens and Wooldridge, 2009) and report the result in Column (3). For this, we first estimate the probability of a firm having parents (i.e., propensity scores). We then weight the regression on the active borrower sample *with* parents by the inverse probability of a firm not having parents. That is, we re-weight the regression for businesses with parents based on the composition of businesses in the baseline sample. We use a gradient boosting decision tree algorithm to improve predictive accuracy in the first step.[17] In Column (3), we show that the result remains similar to the unweighted regression result in Column (2).

One disadvantage of using a decision tree algorithm for the propensity score calculation is the loss of interpretability. For example, the algorithm indicates industry and number of employees are the top two predictors of whether a firm has parents, but the exact relationships remain unknown. For comparison, in Column (4) we simply weight the regression by industry and employee size categories in our baseline sample of businesses without parents. The estimated coefficients on flooded firms become slightly more negative but are still not statistically significant.

3.3.4 Event Studies of Inquiries and Balances

In this section, we exploit more time-granular data in firms' credit reports to examine whether Harvey led firms to apply for credit and if it affected their debt balances. In these analyses, we explore heterogeneity across groups with different characteristics (e.g., firms with and without existing debt). The regressions in this section follow Eq. (4), which allows for the effects of Harvey to evolve over time. Because the full list of interacted coefficients is extensive, we summarize the estimation results in Figure 3. We display results using logged flood depth as the measure of flooding (rather than depth terciles) as it captures variation in flood intensity with a single variable, making the figure easier to interpret. We provide the full regression results and supporting analyses, including the event study results using flood terciles in Appendix B.1.

First, we examine the number of credit inquiries as a measure of a firm's demand for new credit. Each credit report file includes quarterly inquiries for the past three quarters. Our data allow us to construct a pre- and post-Harvey panel of firms where Q4 2016 to Q2 2017 represent the pre-Harvey periods, Q3 2017 is not observed in the data, and Q4 2017 to Q2 2018 represent the post-Harvey periods. Unlike the analysis of impairments which only examined borrowers with loan

[17] The predictor variables include size, age, industry, state, and ZIP-level demographic variables (e.g., mean income, population, education, race, income Gini index). Compared to a logistic regression, a decision tree is better at detecting nonlinear interactions between explanatory variables (Imbens and Wooldridge, 2009). A boosting approach further improves predictive power by implementing a sequential learning procedure where models are built on each other and adjusted by putting particular emphasis on the data points that previous models predicted poorly. The approach alleviates any misspecification concerns for the estimation of propensity scores (Imbens and Wooldridge, 2009). We find qualitatively consistent results using logistic regression.

balances, we extend our attention to the full sample of all 8,219 firms regardless of whether they had any existing debt. We anticipate that credit demand may differ between firms who actively use credit and those who do not and so we examine inquiries by separating the sample into two groups: "non-borrowers" are firms who had no existing debt as of January 2017; "borrowers" are those who did.

Overall, we find that the number of credit inquiries increases significantly in flood intensity (shown in Appendix Table B.1.8). Panel A of Figure 3 plots the event study coefficients of quarterly inquiries on the logged flood depth for both non-borrowers and existing borrowers. The coefficients capture the average change in inquiries relative to Q2 2017 (i.e., approximately a quarter before Harvey) as a function of flood severity, compared to those outside the disaster area. The significant increase in the number of inquiries comes from firms with existing debt. In particular, their inquiries increase significantly in Q1 2018 by 0.01 for every 10% increase in flood depth (e.g., another 2.4 inches more flooding from the median flood depth). In separate regressions, we examine inquiries using flood terciles (instead of logged flood depth), which clarifies the magnitude of the effect: existing borrowers in the most flooded tercile increased their credit inquiries by 50% relative to pre-Harvey levels. The development of inquiries for *non-borrowers*, on the other hand, does not seem to change over time.

Next, we examine the effect of Harvey flooding on loan balances. Information on loan balances is provided on a monthly basis. Accordingly, we construct a balanced panel in which January 2017 to June 2017 represent the pre-Harvey periods, a gap exists in the credit report data from July 2017 to December 2017, and then January 2018 to June 2018 represent the post-Harvey periods. We observe a divergence between existing borrowers and non-borrowers in Panel B of Figure 3.[18] Non-borrowers started borrowing in the post-Harvey periods and their total loan balances increased significantly with flood depth. A 10% increase in flooding from Harvey led to a 1% higher loan balance among these firms. In contrast, flooding from Harvey caused a *decrease* in loan balances

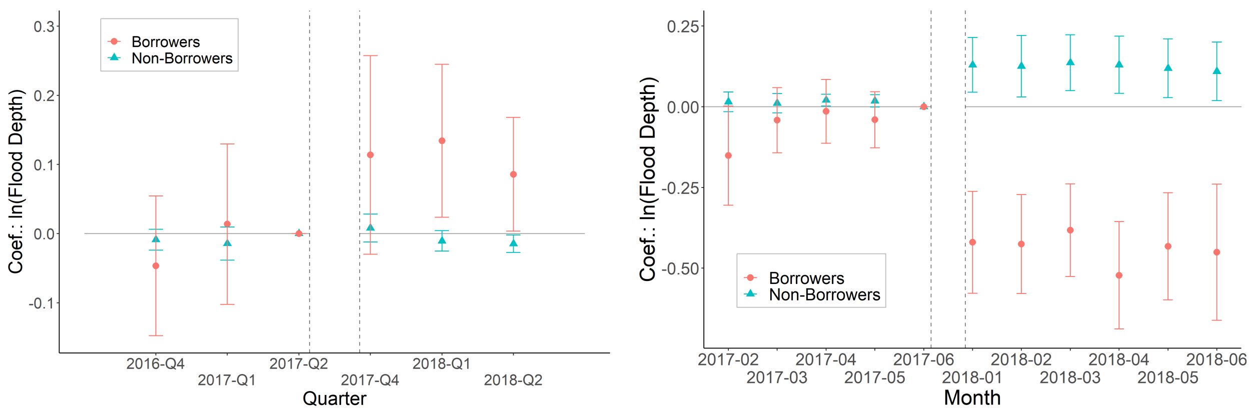
[18]We explore the probability of having any inquiries and the probability of having any debt balances in Table B.1.10 and Figure B.1.3 of Appendix B.1. Similar trends are observed for both borrowers and non-borrowers.

for existing borrowers. The loan balances of existing borrowers consistently stayed at a lower level compared to pre-Harvey periods. A 10% increase in flooding from Harvey caused a 3% *decrease* in loan balances for existing borrowers.[19]

Figure 3: Evolution in Inquiries and Balances

Panel A: Inquiries

Panel B: ln(Balances)



Note: Panel A and Panel B show the evolution of quarterly inquiries and monthly balances, respectively. The figures plot 95% confidence intervals of event study coefficients (i.e., γ_{1t} in Eq. (4)) of inquiries and logged credit balances on the logged flood depth. The coefficients capture the average change in credit outcomes relative to Q2/June 2017 as a function of flood severity, compared to those outside the disaster area. The vertical, dashed lines mark the period during which we do not observe quarterly inquiries or monthly balances. Harvey occurred during that period. For both analyses, we compare two groups: firms with zero balances as of January 2017 ("non-borrowers") and those with positive balances at that date ("borrowers").

Overall, our results in this section suggest that the role of credit during recovery differed across firms, depending on whether they had existing debt when Harvey occurred and how badly they were flooded. Flooding from Harvey led firms *without* existing debt to start borrowing. We do not observe a significant increase in inquiries among these firms, so these firms may have used existing credit lines. Additionally, Harvey led firms *with* existing debt to apply for more credit. Several possibilities could explain why the balances of firms with existing debt fell. The increase in inquiries combined with the decrease in balances suggests that at least some firms were credit constrained.

[19] One possibility is that the observed differences between existing borrowers and non-borrowers is actually capturing effects of firm size. In Figure B.1.4 of the Appendix, we divide the data to compare larger firms (those with at least 10 employees) to smaller firms. We find that flooding increases the inquiries of larger firms, but not smaller firms; however, we do not find significant effects of flooding on the balances of either larger or smaller firms. We conclude that the borrower versus non-borrower comparison is capturing something distinct from firm size, perhaps more closely akin to debt overhang (Myers, 1977).

At the same time, other firms may have decided to deleverage voluntarily due to reduced revenues following Harvey. The survey results in the next section provide additional details regarding the losses that firms in the affected area experienced and how they financed recovery.

4 Business Recovery Survey

4.1 Overview

While the credit report data offer deep insight into one way firms financed the challenges that Harvey created, our survey responses provide a more comprehensive view of Harvey's effects and how firms responded. We describe the ways in which Harvey affected the operations of our surveyed firms (Section 4.2). We then address our core research questions regarding how firms funded losses from the disaster (Section 4.3).

Our primary method of survey distribution was a letter mailed to a random sample of 5,000 businesses in the disaster area. These firms were listed as active businesses in the *ReferenceUSA* database in 2016. The letter included a description of the survey, an identifiable short survey link, and a \$2 bill as a "thank you" for considering participating in the study. In addition, we partnered with local business organizations, such as chambers of commerce, cultural associations, and local SBA offices, to email their members with links to the online survey. We provide a detailed description of the distribution and design of the survey in Appendix A. In total, we received 374 valid responses, 303 of which were complete.[20] To match the filters applied to the credit report data, we drop respondents with more than 500 employees and firms who reported being part of a franchise or a branch of a non-local business. This results in 273 responses for our survey data analysis – 122 through the letter-writing campaign and 151 through business organizations.[21]

[20]We consider a survey "complete" if the respondent progressed to the end of the survey. Respondents were not required to answer every question and any unanswered questions are coded as missing. In addition, many survey questions were conditional on the respondent's earlier answers.

[21]To reduce survivor bias, we designed our survey distribution so that it could capture firms who closed permanently because of Harvey. Specifically, we sent our letter to active firms in the 2016 *ReferenceUSA* data. We also asked that our business organization partners include closed businesses when they sent our survey link to their members. Ten respondents reported having closed permanently.

In Table 6, we report the distributions of local populations, industries, firm sizes (by employee count), and firm ages represented in our survey. We offer comparisons to the same categories for our full Experian sample. The most represented industry is Health Services (31% of survey sample). Most firms had fewer than five employees (46%), about a quarter had between five and nine employees (25%), and only six survey respondents reported having more than 100 workers. The average firm had been operating for 19 years, and about 20% of firms had been in business five years or less. While the distribution of characteristics for our surveyed firms is not identical to those in the Experian sample, they appear quite close by most measures.

Table 6: Characteristics of Firms in the Survey Data and Experian Data

ZIP code population	Survey Pct.	Experian Pct.	Num employees	Survey Pct.	Experian Pct.
0–5,000	4.46	4.58	0-4	46.15	62.31
5,000–20,000	21.56	22.01	5-9	24.54	19.25
20,000–35,000	24.91	27.13	10-19	11.36	9.23
35,000–50,000	29.37	26.12	20-49	11.72	5.44
50,000–75,000	8.92	12.20	50-99	4.03	2.26
75,000+	10.78	7.96	100-499	2.20	1.51
Industry	**Survey Pct.**	**Experian Pct.**	**Firm age (years)**	**Survey Pct.**	**Experian Pct.**
Ag./Forestry/Fishing	2.20	2.12	0-2	9.56	3.19
Construction	8.06	7.77	3-5	10.29	12.82
Manufacturing	2.56	4.16	6-10	15.07	17.69
Transport/Comm./Utilities	4.03	4.45	11-20	23.16	29.19
Wholesale Trade	3.66	4.57	21-30	15.81	24.46
Retail Trade	8.06	12.57	31+	26.10	12.65
Finance/Ins./Real Estate	11.36	9.49			
Food Services	7.33	4.60			
Health Services	31.14	29.07			
All Other Services	19.41	18.42			
Other/Unknown	2.20	2.77			

Note: ZIP Code population is the population in the firm's ZIP Code based on the American Community Survey (ACS, 2016). Industry is based on the first two digits of the firm's SIC code. Number of employees and firm age are self-reported for the survey sample.

We also collected the business credit reports of survey respondents. Experian located the reports of 229 of the 273 survey respondents using the business name and address. We examine loan impairments for this survey population following the regression strategies outlined in Section 3. The results appear qualitatively similar to those in the credit report analysis, though the survey sample has fewer observations and so the coefficient estimates are less precise. For example, loan impairment increased by 9.8 percentage points for surveyed firms in the most flooded areas, relative to non-flooded firms, and this result is significant at the 5% level (Appendix B.2 reports the full results).

4.2 Harvey and Firms' Operations

Many surveyed firms incurred property damage from Harvey, but almost all experienced revenue losses. Approximately 39% of our surveyed firms reported property damage due to flooding and/or strong winds.[22] Nearly 90% of firms lost revenue, most often because of employee disruptions, reduced operations (such as shorter hours or decreased production), and lower customer demand. Fewer firms lost revenue due to utility outages and disruptions to their suppliers.

Respondents estimated the dollar amount of damages and lost revenue from Harvey, shown in Table 7. Property damages appear more costly, as about 40% of firms with property damage had damages of more than \$100,000. However, revenue losses were also substantial: half of firms lost between \$10,000 and \$100,000. We also observe spillover effects – of the firms who had no property damage, 87% still lost revenue and 31% still had not fully recovered a year after the storm.

Table 7: Property Damage and Lost Revenue

	Property damage		Lost revenue	
Loss amount ($)	Freq.	Pct.	Freq.	Pct.
0	167	62.31	28	10.89
1–10K	23	8.58	66	25.68
10K–100K	39	14.55	124	48.25
100K–250K	19	7.09	20	7.78
250K–500K	11	4.10	11	4.28
500K–2M	7	2.61	8	3.11
2M +	2	0.75	0	0.00

Note: Frequencies and percents are tabulated only for respondents who provided an estimated loss amount. Five respondents were unsure about their property loss and sixteen respondents were unsure about their revenue loss.

[22] Other than in coastal areas, Harvey was primarily a flood event. We surveyed firms about both wind and flood hazards; 46% of firms in coastal counties experienced wind damage, compared to 17% in non-coastal counties.

Negatively affected firms varied in their recovery. About 20% reported that they had "fully recovered" less than a month after Harvey. Others continued to struggle – nearly half reported that they still had not fully recovered a year later. About 4% had already permanently closed their business and another 3% said they hadn't closed but would never fully recover.

What types of losses appear to make recovery more difficult? In Table 8, we list different types of losses and the proportion of respondents who experienced each (Column (1)). In Column (2), we report the proportion of firms who had experienced the given loss *and* had fully recovered when the survey was conducted. As another measure of a firm's health, we also report the change in its number of employees between June 30, 2017 and June 30, 2018 (Column (3)). For example, the second row indicates that 61% of sampled firms reported having no property damage. Of these firms, 69% had fully recovered when they took our survey and they had almost no change in employment on average. In contrast, of the 12% with both flood and wind damage (fifth row), only 19% had recovered and they decreased employment by 14% on average. Firms closed for longer time periods tended to struggle more, with large effects for firms closed longer than one week and longer than one month. Compared to other interruptions, firms who experienced utility outages and supplier disruptions appear less likely to have fully recovered.

In summary, the survey offers details about the effects of Harvey which complement the flood depth measures used in the credit report analysis. For example, the delays in recovery may explain the credit impairments and inquiries in Section 3. The survey results also illustrate specific business disruptions which affected both flooded and non-flooded firms – half of our survey sample did not sustain any property damage, but still reported losing revenue because of Harvey. These business disruptions would seem to explain the observed increase in loan impairments among businesses that were not flooded in the disaster area.

4.3 Funding Recovery

Survey respondents reported on the financial resources that they used to fund recovery; 186 respondents (69%) reported having financial needs post-Harvey. Standard models of risk financing for capitally-constrained organizations tend to layer financing in tranches based on loss severity:

Table 8: Losses, Disruptions, and Recovery

	(1) Pct. of Respondents	(2) Recovered Pct.	(3) Mean % ΔEEs
Any loss	91.6	55.1	-1.3
Property damage			
No property damage	61.2	68.6	0.2
Flood damage only	14.7	43.6	0.2
Wind damage only	12.1	43.3	1.2
Both flood and wind damage	12.1	18.8	-14.3
Temporary closure			
$<$ 1 week	32.0	76.9	9.3
1 week – 1 month	46.3	51.3	-4.8
1 – 3 months	9.7	23.5	-15.3
$>$ 3 months	12.0	20.0	-10.7
Business interruption			
Employee disruptions	58.6	53.3	-2.3
Reduced operations	57.9	52.6	-3.0
Lower customer demand	52.4	42.8	-2.7
Utility outage (>48 hours)	34.8	37.0	-6.1
Supplier disruptions	33.0	36.9	-8.2

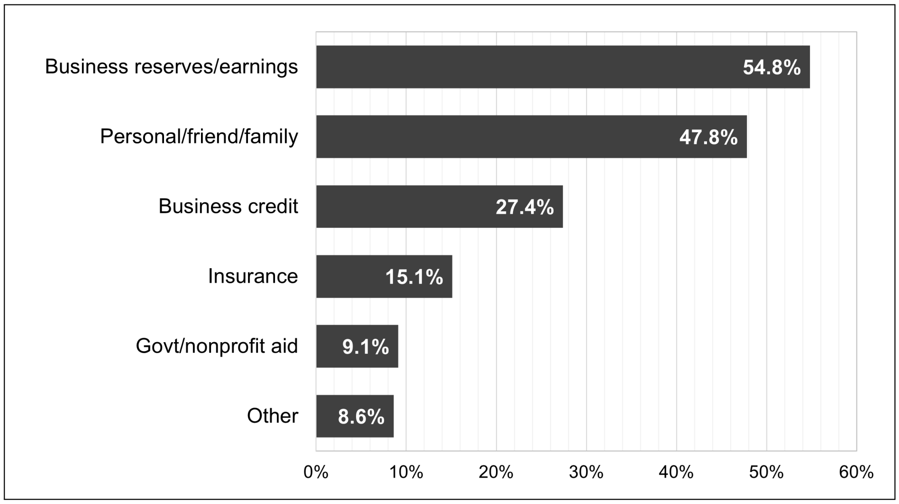
Note: Column (1) is the proportion of surveyed firms who reported experiencing the loss denoted in the respective row. Both Recovered Pct. and Mean % ΔEEs are conditional on having experienced the loss indicated in the row. Recovered Pct. is the proportion of firms who said they were "fully recovered" at the time of the survey. % ΔEEs is the percentage change in the total EEs from June 30, 2017 (pre-Harvey) to June 30, 2018 (post-Harvey). Total EEs are the sum of self-reported full-time and part-time employee counts.

reserves (such as liquid savings) for modest losses, borrowing for moderate losses, and insurance for infrequent, but severe loss events such as hurricanes (Cummins and Mahul, 2008; Kallman, 2008). We find an opposite ordering: even though financial losses were potentially large for many firms, insurance played a relatively minor role in financing recovery. As illustrated in Figure 4, firms were most likely to fund losses with business savings and cash flows (55% of firms).

About a quarter of firms with financial needs used loans to fund their losses. Of these 51 firms, 39 used private business loans, 13 used SBA disaster assistance loans, and 10 used loans from nonprofits (some firms used multiple loan sources). *Ex post* financing frictions are evident: while 93 respondents applied for some type of loan, only half were approved.

Only 15% of firms with financial needs received payments from insurance, which is suggestive of *ex ante* frictions. One reason for this low proportion is that many firms were uninsured, especially for flooding – only about 40% had flood insurance. Business interruption insurance, which replaces

Figure 4: Recovery Funding Sources



Note: Funding sources are reported for the 186 surveyed firms who indicated they needed funds for recovery. "Business credit" includes private loans, SBA loans, and nonprofit loans. "Other" includes financial assistance from other sources, such as crowd funding. Respondents could select multiple sources of funding.

lost revenue when a covered physical loss occurs, was also fairly rare – 22% of respondents had coverage in place.[23] However, even insured businesses often did not receive claims payments: of the 35 firms with lost revenue and business interruption insurance, only eight received a payment.

Formal, arm's-length risk financing structures appear insufficient, as 48% of firms with financial needs ultimately used personal resources (i.e., funds provided by the owner and the owner's family and friends) to help fund recovery. Lee and Persson (2016) study financing from family and friends. They note that while such "informal" financing is often available to the firm at a lower rate than formal financing, it also has undesirable implications. Namely, informal financing erodes the limited liability of the firm, which can lead firms to take on less risky projects. As a result, firms tend to prefer formal financing and so businesses' use of informal resources likely reflects the difficult position of these firms.

[23]Business interruption insurance typically only covers revenue losses resulting from physical damage to insured property (e.g., after a fire, a business loses revenue because it must be closed until the damages are repaired). Thus, revenue losses due to other factors (e.g., lower customer demand) often are not covered. For similar reasons, the COVID-19 pandemic illustrated the limitations of business interruption insurance.

These results connect to our credit report analysis in several ways. They support the finding that firms used credit to fund recovery; however, they also show that borrowing played a limited role relative to other funding strategies, as firms were more likely to use savings, earnings, or personal resources. Firms' limited use of borrowing is due in part to credit constraints: half of the firms who applied for credit were declined. Yet many firms did not apply for credit, which may reflect their inability or unwillingness to service additional debt before their cash flows had fully recovered.[24]

5 Conclusion

Risk management adds value to the firm by reducing the cost of risk. Financing frictions may constrain firms' access to efficient *ex ante* and *ex post* risk management strategies, thereby increasing the cost of risk and the likelihood that shocks result in financial distress. Our study offers new insights on frictions by tracing out the effects of an exogenous negative shock on local firms' finances. We employ a novel approach by analyzing business credit reports using treatment-intensity, difference-in-difference regressions and taking a comprehensive assessment of recovery financing with detailed survey data.

We find that Hurricane Harvey caused financial distress for small firms. Our primary measure of distress is credit delinquencies, which significantly increased for firms in flooded areas. We also document distress for local firms in non-flooded areas, indicating spillover effects on firms who experienced little or no flood damage from the storm. Additionally, we find that flooding affected independent firms differently than those with parents: for a given level of flooding, independent firms were more likely to become delinquent on their debts than firms with parents. Surveyed firms struggled to recover from Harvey – nearly half of negatively affected firms still had not recovered nearly a year later. Recovery challenges stem from both property damages and revenue losses due to employee disruptions, lower customer demand, and reduced operations.

[24] The survey asked affected firms who did not apply for low-interest SBA disaster loans why they did not apply. The most common response was that they were unwilling to take on additional debt (38% of total).

We find that firms rarely use the recovery financing strategies that likely have the lowest costs. Insurance was not a source of recovery financing for most firms. The survey and the credit report data reveal that Harvey increased credit demand but also that many firms were credit constrained. Instead, surveyed businesses commonly turned to informal financing, which may have longer-term effects on firms' strategic decision-making by eroding limited liability protections.

Our findings offer additional evidence on the importance of public policies and market innovations to reduce financing frictions. While much of the policy dialogue has centered on entrepreneurship, our results emphasize how frictions may also increase the costs of adverse events. Firms are exposed to an array of negative shocks; however, severe weather may be of particular importance as the frequency of events like Harvey is increasing (IPCC, 2021). Financial innovation to reduce frictions – including through decentralized finance platforms, improved credit scoring algorithms, and smart contracts – may contribute to more resilient firms.

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Appendix A Survey Methods

A.1 Survey distribution

We distributed the survey using several channels to maximize total responses. Our primary distribution method was a letter mailed to a random sample of 5,000 businesses, which included a description of our survey and a $2 bill as a "thank you" for considering participating in our study. The random sample was stratified by the number of small- and medium-sized businesses reported in each county by the U.S. Census Bureau's County Business Patterns database. This random sample of business addresses was collected from the *ReferenceUSA* database, and few letters were returned as undeliverable. The letter included a simple URL link to the survey, which tagged each respondent as coming from the letter-writing campaign. The letters resulted in 171 survey responses.

Our second method of distribution was to partner with local business organizations, such as chambers of commerce and cultural associations, to email their members with links to our online survey. Contacts in the Houston and Lower Rio Grande Valley district offices of the Small Business Association (SBA) provided a list of 55 locally-active business organizations and made initial introductions. We also hosted a post-Harvey roundtable for business organizations at the Houston Small Business Development Center (SBDC) in July 2018, and made some additional contacts at that event. We provided these organizations with email templates to send to their members, as well as shortened templates to post on social media. We provided both English and Spanish versions of the email and social media templates. These templates included a unique survey URL for each organization, which allowed us to connect each survey response to its distribution source. We asked 72 organizations to distribute the survey, and received a total of 181 usable survey responses from members of 17 of those organizations.

Finally, we received some ad-hoc responses to the survey in unique cases. First, a helpful business owner asked to distribute our survey link to her contacts, and we provided her with a unique URL to do so, resulting in 18 responses. We also received seven responses from a URL shared directly by our SBA contacts. In total for all distribution methods, we received 377 usable responses, 303 of which were 100% complete and 56 of which were less than 50% complete.[25]

We opened the survey to responses on August 24, 2018, which coincided with the one-year anniversary of Hurricane Harvey in Southeast Texas. We sent the email template to our business organization partners on the same day; many of them included our link in their weekly or monthly email newsletter to members. We followed up with our partners in late September and asked them to send a reminder to their members. Our letter was mailed to businesses in early November 2018.

A.2 Survey design

The first page of the survey includes general instructions and guidance. Specifically, we ask subjects to respond with their best estimate or memory and note that we are not asking them to review their records. We provided some informed consent information and a link for more details. On this first page, we also asked whether the respondent was responsible for making insurance decisions and when the business was established. The remainder of the survey comprised eight major sections. We randomized the order of certain sections as long as the randomization did not make the survey confusing. Respondents always began with *Business Demographics*, which requested the firm's name, current address, industry, number of locations, prior flood experience, and some questions on business philosophy.[26]

Following the general business demographics, subjects completed the *Pre-Harvey Financials* section. These questions asked about the financial status of the firm as of June 30, 2017. We asked how business was (five multiple-choice answers, from "Terrible" to "Excellent"), whether the business operated at a profit, break-even, or a loss, and for the number of full-time (30+

[25]There were a total of 430 responses to our survey. We dropped 37 responses which were missing the business name and address, and dropped sixteen which were duplicate responses from the same business. In most cases, these duplicates appeared to be respondents who did not finish their first response and re-started the survey later.

[26]To reduce attrition, none of the survey questions were required—the respondent could continue without answering. We are able to identify questions that were seen but not answered. When feasible, we included an "Unsure" option and/or an "Other" option with a text input box to provide alternative responses.

hours/week) and part-time (¡30 hours/week) employees. We also asked respondents to estimate the replacement cost of five asset categories: (1) Buildings or other structures, (2) Furnishings, (3) Equipment or machinery, (4) Product inventory, and (5) Vehicles used in the business. Respondents chose a range of possible asset values from a drop-down menu with thirteen options, from "Less than $10,000" to "More than $5,000,000." After *Pre-Harvey Financials*, we randomized the order of certain sections. We list the remaining sections in a logical order for clarity.

The *Pre-Harvey Risk Management* section asked respondents about the risk management practices they had in place on June 30, 2017. We did not expect respondents to know specifics of their insurance contracts, so we asked for the proportion of assets insured against wind and flood—None, Some insured (under 50%), Most insured (at least 50%), and All insured (100%). We also asked whether wind insurance was provided by the Texas Windstorm Insurance Association (TWIA) and whether flood insurance was provided by the National Flood Insurance Program (NFIP). For those who had wind and/or flood insurance, we asked whether the policy included coverage for business interruption (which we summarized as coverage for "lost profits while your business is closed due to damage," with an external link to an article by the Insurance Information Institute). We also asked about non-insurance risk management, specifically whether the business had a written emergency response plan, cash reserves (i.e., a "rainy day" fund), or an "emergency" business credit card or line of credit. Here, we also asked for address of the business's main location if different from the address provided in *Business Demographics*, the type of location (e.g., residence, office/retail/restaurant, warehouse/industrial, or other), whether this location was on the ground floor, and whether the location was owned or leased.

Later in the survey, we asked about the firm's changes in risk management following Hurricane Harvey in the *Post-Harvey Risk Management* section. We asked whether the respondent elected to purchase (or modify, if they had coverage prior to Harvey) wind, flood, or business interruption insurance. We also asked about changes in non-insurance risk management, such as an emergency response plan, cash reserves, emergency credit, moving to a lower-risk location, or making physical changes to the current location.

In the *Harvey Effects* section, we first asked about the types of damage or disruptions potentially caused by Harvey, such as flood damage, wind damage, temporary or permanent closure, utility outages, decreased customer demand, etc. We then asked whether overall effect of Harvey was positive, negative, or neutral. For positively affected businesses, we asked for specifics about the positive effects (e.g., new revenue, competitors negatively affected, other, etc.). For firms who experienced property damage, we asked respondents to estimate the total amount of damage and the amount of wind or flood insurance payments for the physical damage. For firms who reported effects that reduced revenue (e.g., closure, lower customer demand, etc.), we asked for the estimated amount of revenue lost and the amount of insurance payments for the lost revenue (e.g., business interruption insurance).

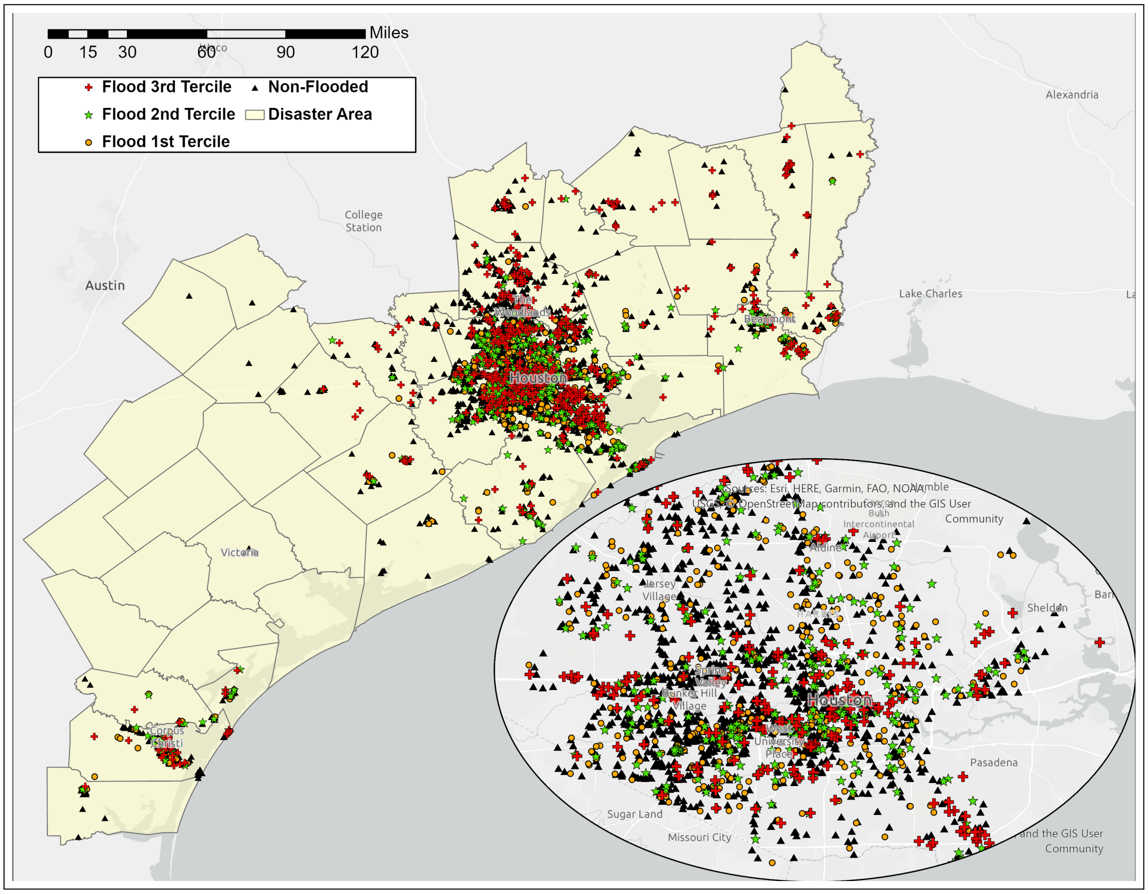
We asked the same employee and profitability questions as pre-Harvey in the *Post-Harvey Financials* section. In addition, we asked respondents how their firm addressed financial needs (if any) resulting from Hurricane Harvey. Our financing options included business cash flow, business credit, personal resources (e.g., personal savings/credit, friends/family), insurance payments, SBA disaster assistance loans, other government assistance, nonprofit loans/grants, and crowd funding. We also asked a number of questions about applying for and approvals/denials of SBA disaster assistance loans, and the timing of any disaster loan funds. For firms who indicated they addressed financial needs with insurance payments, we asked when the first insurance payments were received. Finally, we asked respondents to judge whether the business had "fully recovered" from Harvey, and how long the recovery took (or how much longer they expect, if the business hadn't fully recovered).

The survey concluded with the Respondent Demographics section, where we asked about company title, age, sex, race, education, and political affiliation. We also asked the "General Risk Question" (GRQ) of Dohmen et al. (2011) This question asks respondents to self-report their risk attitude on a scale of zero ("Not at all willing to take risks") to ten ("Very willing to take risks"). The GRQ has been shown to correlate significantly with risk preferences and risky behaviors.

Appendix B Additional Tables and Figures

B.1 Additional Tables and Figures for Section 3

Figure B.1.1: Studied Firms in Disaster Area: Flood Terciles vs. Non-Flooded

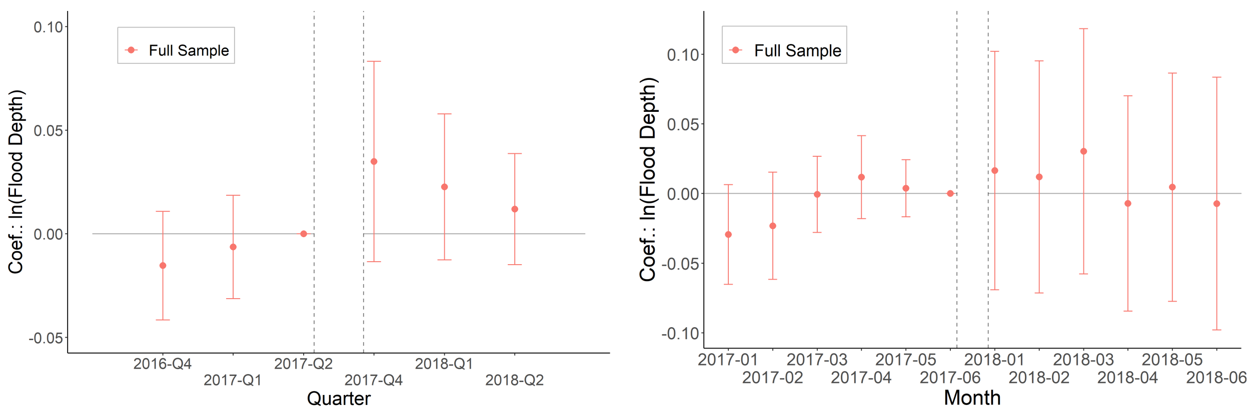


Note: Major Disaster Declaration DR-4332-TX designated 41 counties to receive federal aid (FEMA, 2017b) for Hurricane Harvey. We refer to these counties as the "disaster area" (yellow area). We group flooded firms into terciles based on the flood depth at their location estimated by FEMA ("Flood Depth"; FEMA, 2018). The first tercile (yellow circle) includes firms in areas with less than 1.7 feet of flooding. The third tercile (red cross) includes firms in areas flooded 2.7 feet or more.

Figure B.1.2: Evolution in Inquiries and Balances, Full Sample

Panel A: Inquiries

Panel B: ln(Balances)



Note: Figures provide general support for the parallel trends assumption. None of the pre-Harvey coefficients are significantly different from zero. The figure in Panel A plots 95% confidence interval of event study coefficients of quarterly inquiries on the logged flood depth. The quarterly before Harvey, Q2 2017, is the reference period. The figure in Panel B plot 95% confidence interval of event study coefficients of logged monthly credit balances on the logged flood depth. The coefficients capture the average change in credit outcomes relative to Q2/June 2017 as a function of flood severity, compared to those outside the disaster area. The vertical, dashed lines mark the period during which we do not observe quarterly inquiries or monthly balances. Harvey occurred during that period. The regression models follow Eq. (4).

Table B.1.1: Pre- and Post-Harvey Trends: Small Business Activities

	Establishments				
	(1) Total Number	(2) Entry Rate	(3) Exit Rate	(4) Death Rate	(5) Employment
I(Harvey Disaster Area) ×					
I(Three Years Prior)	−5,083.341	0.007	−0.002	−0.001	−7,466.615
	(6,083.709)	(0.006)	(0.004)	(0.004)	(10,986.830)
I(Two Years Prior)	−5,183.057	0.006	−0.001	0.0001	−7,524.380
	(5,980.579)	(0.005)	(0.004)	(0.003)	(10,876.900)
I(One Year Prior)	−5,946.895	0.004	0.011*	0.007	−9,269.130
	(5,976.881)	(0.005)	(0.006)	(0.005)	(10,859.710)
I(One Year After)	−4,164.090	0.004	0.007	0.006	−9,930.771
	(5,911.394)	(0.004)	(0.005)	(0.004)	(10,862.030)
State-MSA FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster by State-MSA	Yes	Yes	Yes	Yes	Yes
N	3,985	3,985	3,985	3,985	3,985
R^2	0.618	0.690	0.487	0.470	0.576

Note: Table presents county-level analysis of small business activities following Hurricane Harvey on counties we draw from for credit report analysis. We estimate:

$$\begin{aligned} y_{jt} = \gamma_0 &+ \sum_t \gamma_{1t} \mathrm{I}_t(\text{Year}) \times \mathrm{I}_j(\text{Harvey Disaster Area}) \\ &+ \sum_t \gamma_{2t} \mathrm{I}_t(\text{Year}) \times \mathrm{I}_j(\text{Outside Disaster Area, TX}) + \mathrm{FE}_m + \mathrm{FE}_t + \varepsilon_{jt}. \end{aligned} \tag{A1}$$

where j indexes counties and t indexes year. March 2017 serves as reference period. The models include year fixed effects and state-MSA fixed effects. Disaster area represents being one of the 41 counties that were eligible for federal aid in the presidential disaster declaration DR-4332-TX for Hurricane Harvey (FEMA, 2017b). Regressions report robust standard errors clustered by state-MSA. Data are from Business Dynamics Statistics and Nonemployer Statistics of the U.S. Census Bureau (2018a,b). The data include sole proprietors with no paid employees and establishments of firms with fewer than 500 employees. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.2: Post-Sandy Trends: Small Business Activities

	Establishments				
	(1) Total Number	(2) Entry Rate	(3) Exit Rate	(4) Death Rate	(5) Employment
I(Sandy Disaster Area) ×					
I(One Year After)	2,559.999	0.0003	0.002	0.003*	2,119.587
	(11,322.770)	(0.002)	(0.001)	(0.002)	(23,747.000)
I(Two Years After)	4,251.429	−0.001	0.006***	0.005***	3,390.843
	(11,887.000)	(0.002)	(0.001)	(0.001)	(24,589.810)
I(Three Years After)	4,907.492	−0.003**	0.007***	0.005***	5,172.876
	(12,076.800)	(0.002)	(0.001)	(0.001)	(25,372.730)
State-MSA FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster by State-MSA	Yes	Yes	Yes	Yes	Yes
N	12,556	12,556	12,556	12,556	12,556
R^2	0.607	0.269	0.192	0.152	0.555

Note: Table presents county-level analysis of small business activities following Hurricane Sandy. We estimate:

$$y_{jt} = \gamma_0 + \sum_t \gamma_{1t} \mathrm{I}_t(\text{Year}) \times \mathrm{I}_j(\text{Sandy Disaster Area}) + \sum_t \gamma_{2t} \mathrm{I}_t(\text{Year}) \times \mathrm{I}_j(\text{Outside Disaster Area, NY/NJ/CT}) + \mathrm{FE}_m + \mathrm{FE}_t + \varepsilon_{jt}. \quad \text{(A2)}$$

where j indexes counties and t indexes year. March 2012 serves as reference period. The models include year fixed effects and state-MSA fixed effects. Disaster area represents counties eligible for federal aid in the presidential disaster declaration DR-4085-NY, DR-4086-NJ, and DR-4087-CT for Hurricane Sandy. Regressions report robust standard errors clustered by state-MSA. Data are from Business Dynamics Statistics and Nonemployer Statistics of the U.S. Census Bureau (2018a,b). The data include sole proprietors with no paid employees and establishments of firms with fewer than 500 employees. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.3: Post-Katrina Trends: Small Business Activities

	Establishments				
	(1) Total Number	(2) Entry Rate	(3) Exit Rate	(4) Death Rate	(5) Employment
I(Katrina Disaster Area) ×					
I(One Year After)	−247.158	0.005*	0.018	0.009	−1,656.876
	(384.206)	(0.003)	(0.015)	(0.009)	(1,012.704)
I(Two Years After)	−348.512	0.020**	−0.009***	−0.005**	−1,111.076
	(419.381)	(0.008)	(0.003)	(0.002)	(938.074)
I(Three Years After)	−116.655	0.007***	−0.003	0.001	−912.544
	(443.280)	(0.002)	(0.003)	(0.003)	(942.750)
State-MSA FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster by State-MSA	Yes	Yes	Yes	Yes	Yes
N	12,568	12,568	12,568	12,568	12,568
R^2	0.611	0.368	0.249	0.269	0.572

Note: Table presents county-level analysis of small business activities following Hurricane Katrina. We estimate:

$$\begin{aligned} y_{jt} = \gamma_0 &+ \sum_t \gamma_{1t} \mathrm{I}_t(\text{Year}) \times \mathrm{I}_j(\text{Katrina Disaster Area}) \\ &+ \sum_t \gamma_{2t} \mathrm{I}_t(\text{Year}) \times \mathrm{I}_j(\text{Outside Disaster Area, LA/MS/AL}) + \mathrm{FE}_m + \mathrm{FE}_t + \varepsilon_{jt}. \quad \text{(A3)} \end{aligned}$$

where j indexes counties and t indexes year. March 2005 serves as reference period. The models include year fixed effects and state-MSA fixed effects. Disaster area represents counties eligible for federal aid in the presidential disaster declaration DR-1603-LA, DR-1604-MS, and DR-1605-AL for Hurricane Katrina. Regressions report robust standard errors clustered by state-MSA. Data are from Business Dynamics Statistics and Nonemployer Statistics of the U.S. Census Bureau (2018a,b). The data include sole proprietors with no paid employees and establishments of firms with fewer than 500 employees. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.4: Share of Balances that are Impaired, Full Sample

	PctImpaired						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Post-Harvey) ×							
I(No Flood, Disaster Area)	0.013**	0.013**	0.010*	0.024***	0.024***	0.020***	0.029***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
I(Flood 1st Tercile)	0.020***	0.020***	0.019***	0.033***			
	(0.006)	(0.006)	(0.006)	(0.007)			
I(Flood 2nd Tercile)	0.025***	0.025***	0.024***	0.038***			
	(0.008)	(0.008)	(0.008)	(0.009)			
I(Flood 3rd Tercile)	0.030***	0.030***	0.027***	0.041***			
	(0.008)	(0.008)	(0.008)	(0.009)			
I(Flooded)					0.037***		
					(0.007)		
ln(Flood Depth)						0.024***	
						(0.005)	
I(Flooded, Remote)							0.031***
							(0.009)
I(TX)				−0.022***	−0.022***	−0.018**	−0.022***
				(0.008)	(0.008)	(0.007)	(0.008)
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	8,219	8,219	8,219	8,219	8,219	8,219	8,219
Firm-Year Obs	16,438	16,438	16,438	16,438	16,438	16,438	16,438
R^2	0.001	0.735	0.736	0.736	0.736	0.736	0.736

Note: Table reports the full sample estimation results of impairment analysis. Dependent variable is the share of loan balances that are not paid on time within the agreed terms for a firm's continuously reported loans ($PctImpaired_i$). Column 1 shows the results without any fixed effects; the regression in Column 2 includes firm fixed effects; Column 3 adds in control variables. Our preferred model is in Column 4, in which we also include an indicator for firms located in Texas to control for any potential systemic differences between these firms and those in other states. Disaster area represents the 41 counties that were declared the disaster area eligible for federal aid in the presidential disaster declaration. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.5: Share of Balances that are Delinquent, Collections, and Legal Filings, Full Sample

	PctDelinquent					
	(1) 1-30 days	(2) 31-60 days	(3) 61-90 days	(4) 90+ days	(5) ln(Collection)	(6) ln(Legal)
I(Post-Harvey) ×						
I(No Flood, Disaster Area)	0.011**	0.002	0.005**	0.005	0.0005	−0.031
	(0.005)	(0.003)	(0.002)	(0.004)	(0.032)	(0.022)
I(Flood 1st Tercile)	0.011**	0.010***	0.007***	0.005	0.087**	−0.001
	(0.005)	(0.003)	(0.002)	(0.004)	(0.041)	(0.028)
I(Flood 2nd Tercile)	0.018***	0.006*	0.009***	0.005	−0.098**	−0.037
	(0.006)	(0.004)	(0.003)	(0.004)	(0.040)	(0.027)
I(Flood 3rd Tercile)	0.025***	−0.0002	0.011***	0.005	0.024	−0.042
	(0.005)	(0.004)	(0.003)	(0.006)	(0.049)	(0.035)
I(TX)	−0.012**	−0.001	−0.004	−0.005	0.024	0.011
	(0.005)	(0.003)	(0.003)	(0.005)	(0.034)	(0.029)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	8,219	8,219	8,219	8,219	8,219	8,219
Firm-Year Obs	16,438	16,438	16,438	16,438	16,438	16,438
R^2	0.656	0.545	0.660	0.798	0.919	0.946

Note: Table reports the full sample estimation results of impairment decomposition analysis. Dependent variables from Column 1 to 4 are the share of a firm's continuously reported loan balances that is delinquent ($PctDelinquent_i$) at four different levels: 1-30 days delinquent, 31-60 days delinquent, 61-90 days delinquent, and over 90 days delinquent. Dependent variable in Column 5 is the logged amount placed for collections in the last seven years ($ln(Collections_i)$). Dependent variable in Column 6 is the logged liability amount of legal filings (*i.e.*, tax liens and judgments) in the last seven years ($ln(Legal_i)$). The models include firm fixed effects, year fixed effects, and control variables. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.6: Ratio of Impaired Loans, Number of Loans

		PctDelinquent, Number of Loans				
	(1)	(2)	(3)	(4)	(5)	(6)
	PctImpaired	1-30 days	31-60 days	61-90 days	90+ days	Derogatory
I(Post-Harvey) ×						
I(No Flood, Disaster Area)	0.014	0.023	−0.013	−0.0001	0.005	−0.001**
	(0.015)	(0.016)	(0.008)	(0.008)	(0.010)	(0.001)
I(Flood 1st Tercile)	0.068***	0.044**	0.019**	0.005	−0.001	0.001
	(0.023)	(0.019)	(0.009)	(0.007)	(0.011)	(0.001)
I(Flood 2nd Tercile)	0.068***	0.041**	0.025***	−0.001	0.001	0.001
	(0.018)	(0.017)	(0.010)	(0.009)	(0.011)	(0.001)
I(Flood 3rd Tercile)	0.068***	0.042***	0.022**	0.009	−0.003	−0.002
	(0.019)	(0.016)	(0.010)	(0.007)	(0.009)	(0.002)
I(TX)	−0.002	−0.014	0.002	0.003	0.007	0.0001
	(0.019)	(0.016)	(0.008)	(0.008)	(0.011)	(0.0003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	2,614	2,614	2,614	2,614	2,614	2,614
Firm-Year Obs	5,228	5,228	5,228	5,228	5,228	5,228
R^2	0.774	0.670	0.579	0.677	0.835	0.971

Note: Dependent variable in Column 1 is the the number of loans that are not paid on time within the agreed terms divided by the total number of loans for a firm. Dependent variables from Column 2 to 6 are the ratio of a firm's number of loans that are delinquent at five different levels: 1-30 days delinquent, 31-60 days delinquent, 61-90 days delinquent, over 90 days delinquent, and having derogatory comments. Derogatory comments here include bankruptcy, judgment, lien, etc. The mean and median number of loans for a firm is 3.5 and 2, respectively. The models include time fixed effects, firm fixed effects, and control variables. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.7: Summary Statistics: Firms with Parents

Variable	Total	Outside	No Flood, Disaster Area	Flooding: 1st Tercile (1, 1.69 ft]	Flooding: 2nd Tercile (1.69, 2.68 ft]	Flooding: 3rd Tercile >2.68 ft
Full Sample with Parents						
No. of Firms	1,173	443	456	89	82	103
Employees	18.91	21.17	18.41	17.15	16.30	15.06
	[6]	[7]	[6]	[5]	[5]	[6]
	(43.30)	(50.61)	(40.22)	(29.05)	(44.32)	(29.83)
Total Balance ($)	37,479	69,795	14,910	7,622	6,926	52,830
	[0]	[0]	[0]	[0]	[0]	[0]
	(346,793)	(476,341)	(174,616)	(36,368)	(41,772)	(501,788)
Active Borrower Sample with Parents						
No. of Firms	313	134	125	22	13	19
Employees	37.58	39.89	36.22	29.50	42.15	36.58
	[10]	[10]	[10]	[13]	[9]	[16]
	(73.16)	(82.73)	(65.68)	(39.07)	(101.05)	(61.23)
Total Balance ($)	140,245	227,077	54,262	30,777	43,685	286,358
	[3,100]	[4,600]	[3,100]	[1,100]	[1,300]	[3,200]
	(661,295)	(847,269)	(331,257)	(69,254)	(100,191)	(1,164,573)
PctImpaired	0.16	0.18	0.15	0.07	0.11	0.18
	[0.01]	[0.05]	[0.00]	[0.00]	[0.00]	[0.00]
	(0.26)	(0.28)	(0.25)	(0.15)	(0.24)	(0.30)

Notes: Sample includes businesses with fewer than 500 employees that have parents. The values in the first, second, and third rows under each variable are means, [medians], and (standard deviations), respectively. Active borrowers include firms that have positive loan balances on both June 30, 2017 and June 30, 2018. These filters create a smaller "Active Borrower Sample". All variables are from the firm's credit report on June 30, 2017.

Table B.1.8: Post-Harvey Effects: Inquiries and Balances

	Quarterly Inquiries			ln(Monthly Balances)		
	(1)	(2)	(3)	(4)	(5)	(6)
I(Post-Harvey) ×						
I(No Flood, Disaster Area)	0.014*	−0.002	0.064*	−0.055	0.042	−0.344***
	(0.009)	(0.007)	(0.034)	(0.046)	(0.037)	(0.098)
ln(Flood Depth)	0.030**	0.002	0.122***	0.014	0.112***	−0.389***
	(0.013)	(0.008)	(0.030)	(0.042)	(0.040)	(0.082)
I(TX)	−0.015	−0.0003	−0.062	0.005	−0.030	0.141
	(0.017)	(0.010)	(0.056)	(0.055)	(0.053)	(0.133)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Non-Borrowers	Borrowers	Full	Non-Borrowers	Borrowers
Firm-Time Obs	49,314	36,420	12,894	98,628	66,770	23,639
R^2	0.583	0.325	0.590	0.919	0.594	0.790

Note: Dependent variables from Columns 1 to 3 are quarterly inquiries from Q4 2016 to Q2 2017 and from Q4 2017 to Q2 2018. Dependent variables from Columns 4 to 6 are logged monthly balances from January to June for 2017 and from January to June 2018. For both analyses, we study the full sample and divide them into two groups: firms with zero balances as of January 2017 ("non-borrowers") and those with positive balances at that date ("borrowers"). For this reason, we drop January 2017 in Columns 5 and 6. We estimate standard treatment effects regressions as in Eq. (3). The models include time fixed effects and firm fixed effects. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table B.1.9: Post-Harvey Effects: Inquiries and Balances by Flood Terciles

	Quarterly Inquiries			ln(Monthly Balances)		
	(1)	(2)	(3)	(4)	(5)	(6)
I(Post-Harvey) ×						
I(No Flood, Disaster Area)	0.011	0.002	0.036	0.040	0.139***	−0.309**
	(0.012)	(0.009)	(0.042)	(0.053)	(0.038)	(0.143)
I(Flood 1st Tercile)	−0.002	0.009	−0.044	0.167**	0.179***	−0.097
	(0.016)	(0.016)	(0.048)	(0.072)	(0.050)	(0.178)
I(Flood 2nd Tercile)	0.006	−0.003	0.035	0.219***	0.262***	−0.052
	(0.020)	(0.008)	(0.070)	(0.084)	(0.082)	(0.171)
I(Flood 3rd Tercile)	0.058***	0.018	0.179***	0.074	0.270***	−0.645***
	(0.022)	(0.015)	(0.059)	(0.077)	(0.060)	(0.220)
I(TX)	−0.012	−0.004	−0.035	−0.082	−0.118**	0.106
	(0.019)	(0.011)	(0.062)	(0.061)	(0.055)	(0.162)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Non-Borrowers	Borrowers	Full	Non-Borrowers	Borrowers
Firm-Time Obs	49,314	36,420	12,894	98,628	66,770	23,639
R^2	0.583	0.325	0.590	0.919	0.594	0.790

Note: Dependent variables from Columns 1 to 3 are quarterly inquiries from Q4 2016 to Q2 2017 and from Q4 2017 to Q2 2018. Dependent variables from Columns 4 to 6 are logged monthly balances from January to June for 2017 and from January to June 2018. For both analyses, we study the full sample and divide them into two groups: firms with zero balances as of January 2017 ("non-borrowers") and those with positive balances at that date ("borrowers"). For this reason, we drop January 2017 in Columns 5 and 6. We estimate standard treatment effects regressions as in Eq. (3). The models include time fixed effects and firm fixed effects. Regressions report robust standard errors clustered by county. Since the dependent variables are logged values of total loan balances from Columns 4 to 6, the most accurate interpretation of the flood effect in each tercile is to exponentiate the coefficients and then subtract one. For example, the coefficient on I_t(Post-Harvey) × I_i(Flood 3rd Tercile) is 0.27 for non-borrowers, which indicates that Harvey caused an increase of $(e^{0.27} - 1) \times 100 = 31\%$ in loan balances. Similarly, Harvey caused a decrease of $|(e^{-0.645} - 1) \times 100| = 48\%$ in loan balances for borrowers in the most flooded tercile. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

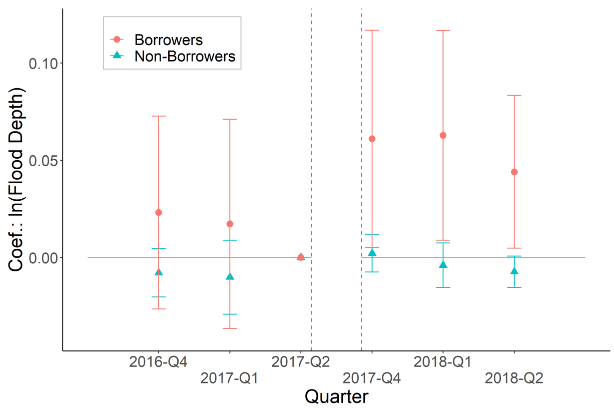
Table B.1.10: Post-Harvey Effects: Probability of Having Inquiries and Balances

	I(Quarterly Inquiries)			I(Monthly Balances)		
	(1)	(2)	(3)	(4)	(5)	(6)
I(Post-Harvey) ×						
I(No Flood, Disaster Area)	0.006	0.004	0.014	−0.005	0.007	−0.038***
	(0.004)	(0.004)	(0.016)	(0.007)	(0.006)	(0.013)
ln(Flood Depth)	0.013**	0.003	0.043***	0.004	0.013**	−0.037***
	(0.006)	(0.004)	(0.015)	(0.006)	(0.006)	(0.012)
I(TX)	−0.005	−0.004	−0.006	0.001	−0.004	0.016
	(0.007)	(0.005)	(0.020)	(0.007)	(0.007)	(0.017)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Non-Borrowers	Borrowers	Full	Non-Borrowers	Borrowers
Firm-Time Obs	49,314	36,420	12,894	98,628	66,770	23,639
R^2	0.460	0.294	0.461	0.893	0.587	0.543

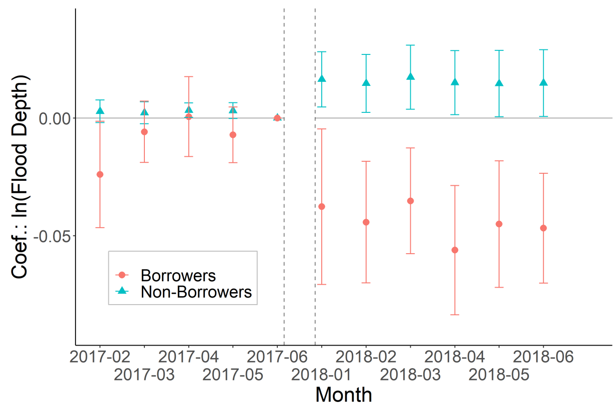
Note: Dependent variables from Column 1 to 3 are dummies indicating whether a firm had any quarterly inquiries from Q4 2016 to Q2 2017 and from Q4 2017 to Q2 2018. Dependent variables from Column 4 to 6 are dummies indicating whether a firm had any monthly balances from January to June for 2017 and from January to June 2018. For both analyses, we study the full sample and divide them into two groups: firms with zero balances as of January 2017 ("non-borrowers") and those with positive balances at that date ("borrowers"). For this reason, we drop January 2017 in Columns 5 and 6. We estimate standard treatment effects regressions as in Eq. (3). The models include time fixed effects and firm fixed effects. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Figure B.1.3: Evolution in Probability of Having Inquiries and Balances

Panel A: Probability of Having Inquiries



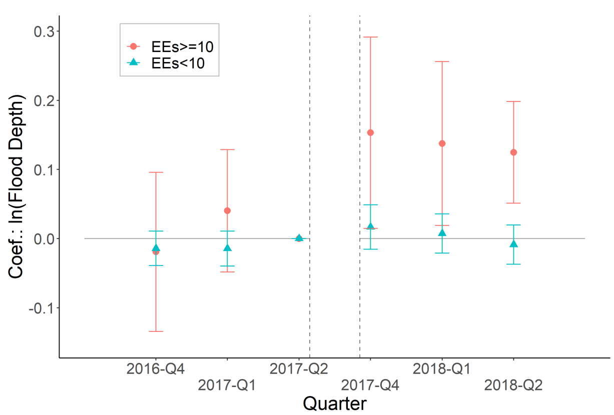
Panel B: Probability of Having Debt Balances



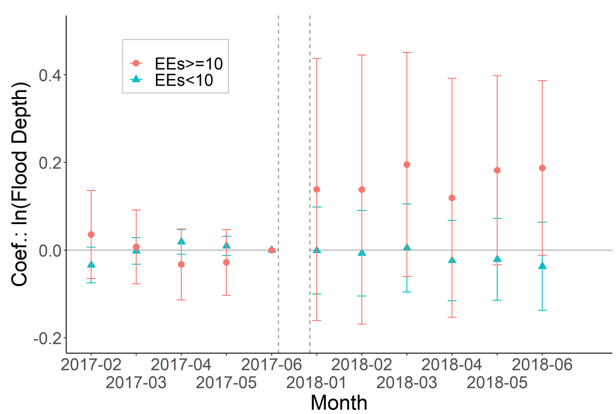
Note: We explore the probability of having any inquiries and the probability of having any debt balances following Hurricane Harvey. The figure in Panel A plots 95% confidence interval of event study coefficients of the probability of having quaterly inquires on the logged flood depth. The quarterly before Harvey, Q2 2017, is the reference period. The vertical, dashed lines mark the period Q3 2017, during which we do not observe quarterly inquiries. Harvey occurred during that period. The figure in Panel B plots 95% confidence interval of event study coefficients of the probability of having monthly credit balances on the logged flood depth. June 2017 serves as the reference period. The vertical, dashed lines mark the period July to December 2017, during which we do not observe monthly DBT and balances. Harvey occurred during that period. The regression models follow Eq. (4).

Figure B.1.4: Evolution in Inquiries and Balances by Firm Size

Panel A: Inquiries



Panel B: ln(Balances)



Note: We divide the full sample into two groups: firms with fewer than 10 employees and those with at least 10 employees. Panel A shows the evolution of quarterly inquiries. The figure plots the 95% confidence interval of event study coefficients of quarterly inquiries on the logged flood depth. The quarter before Harvey, Q2 2017, is the reference period. The vertical dashed lines mark the period Q3 2017, during which we do not observe quarterly inquiries. Harvey occurred during that period. Panel B shows the evolution of monthly balances. The figure plots the 95% confidence interval of event study coefficients of logged monthly credit balances on the logged flood depth. Coefficients can be interpreted as the effect of flooding relative to the firms outside the disaster area and relative to June 2017. The vertical dashed lines mark the period July to December 2017, during which we do not observe monthly balances. Harvey occurred during that period. The regression models follow Eq. (4).

B.2 Credit Report Analysis of Survey Sample

In Table B.2.1, we apply our credit report analyses (Section 3) to the survey sample of 273 firms. After filtering out duplicate credit reports and firms with no 2017 credit record, we have a sample of 229 firms. Specifically, we estimate:

$$
\begin{aligned}
y_{it} = \beta_0 &+ \beta_1 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Outside Disaster Area}) \\
&+ \beta_2 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Flood} \leq \text{Median}) \\
&+ \beta_3 \mathrm{I}_t(\text{Post-Harvey}) \times \mathrm{I}_i(\text{Flood} > \text{Median}) \\
&+ \theta \mathrm{I}_t(\text{Post-Harvey}) \times X_i + \mathrm{FE}_i + \mathrm{FE}_t + \varepsilon_{it}
\end{aligned} \tag{A4}
$$

There are two major differences from our estimations in Section 3. First, due to a small number of firms outside the disaster area (19 firms), we use firms in the disaster area but was not identified as flooded ("I(No Flood, Disaster Area)") as our reference group. Second, for similar reasons we only divide flooded firms based on whether their flood depth is below or above the median value of 2.1 feet (instead of dividing into terciles).

Table B.2.1 indicates that surveyed firms that experienced above-median flood had significant increases in the share of impaired balances, particularly balances that are 60-90 days delinquent and over 90 days delinquent. However, note that the small sample size of our surveyed firms means that our regression results might be heavily relied on a small number of firms that had any changes on the credit outcomes of interest, or that there might be insufficient power to detect any flood effects. For example, the number of firms in the control group that had any changes in the share of balances that are 61-90 days delinquent, over 90 days delinquent, collections, and legal filings (Columns 4 to 7) are 4, 7, 4, and 1, respectively. The observed changes are even rarer for firms with a above-median flood depth. For them, the number of firms that had any changes on these outcomes are 2, 2, 2, and 0, respectively.

Table B.2.1: Share of Delinquent Balances, Unpaid Collections, and Legal Filings: Survey Sample

		PctDelinquent					
	(1) PtcImpaired	(2) 1-30 days	(3) 31-60 days	(4) 61-90 days	(5) 90+ days	(6) ln(Collection)	(7) ln(Legal)
I(Post-Harvey) ×							
I(Outside Disaster Area)	0.001	0.062	−0.003	−0.087	0.029	−0.005	0.116
	(0.137)	(0.093)	(0.072)	(0.078)	(0.019)	(0.251)	(0.076)
I(Flood ≤ Median)	−0.010	0.016	−0.004	−0.010	−0.012	−0.140	0.004
	(0.079)	(0.055)	(0.015)	(0.008)	(0.020)	(0.164)	(0.006)
I(Flood > Median)	0.098**	0.066	−0.032	0.023***	0.041***	0.191	0.011
	(0.046)	(0.043)	(0.033)	(0.006)	(0.011)	(0.216)	(0.009)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by County	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firm	105	105	105	105	105	105	105
Firm-Time Obs	210	210	210	210	210	210	210
R^2	0.842	0.799	0.571	0.693	0.604	0.916	1.000

Note: Table reports the survey sample estimation results of impairment analysis. The reference group in these regressions is firms in the disaster area but was not identified as flooded. We only keep firms with positive continuously reported loan balances (i.e., those that have had at least one update within the past three months, and also at least one other time in the prior 36 months) on both June 30, 2017 and June 30, 2018. We restrict the sample in this way in the impairment analysis as only firms that are actively borrowing can have loan impairments. Dependent variable in Column 1 is the share of loan balances that are not paid on time within the agreed terms for a firm's continuously reported loans ($PctImpaired_i$). Dependent variables from Column 2 to 5 are the share of a firm's continuously reported loan balances that is delinquent ($PctDelinquent_i$) at four different levels: 1-30 days delinquent, 31-60 days delinquent, 61-90 days delinquent, and over 90 days delinquent. Dependent variable in Column 6 is the logged amount placed for collections in the last seven years ($ln(Collections_i)$). Dependent variable in Column 7 is the logged liability amount of legal filings (*i.e.*, tax liens and judgments) in the last seven years ($ln(Legal_i)$). The models include firm fixed effects, year fixed effects, and control variables. We also control for the distribution method of a survey, i.e., whether through the letter-writing campaign or business organizations. Regressions report robust standard errors clustered by county. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.