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Financing Negative Shocks: Evidence from Hurricane Harvey

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Abstract

We examine the effects of a severe climate event on local firms. Our data include 8,218 business credit reports and a detailed survey of 273 businesses in the area affected by Hurricane Harvey. Delinquent credit balances doubled in areas with the worst flooding, although nonflooded areas also had significant credit impairments. Only independent businesses showed signs of distress; subsidiaries of larger firms did not. Firms were largely uninsured and often were denied credit postdisaster. Many funded recovery informally, such as through friends and family. Our findings suggest that several financial frictions compound the challenges posed by a severe climate event.

I. Introduction

Severe climate events pose an increasing challenge for local businesses. In the U.S. alone, 31 disasters each exceeded $1 billion in damages in the 1980s; 128 such disasters occurred in the 2010s (inflation-adjusted, NOAA (2022)). Managing this growing risk—whether through insurance, borrowing for recovery, or paying for repairs out-of-pocket—requires resources. However, financial constraints often hinder local businesses, potentially crowding out ex ante risk management

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(Rampini and Viswanathan (2010)) and limiting access to ex post financing such as credit (Froot, Scharfstein, and Stein (1993)). Consequently, constrained firms may be especially susceptible to distress following a shock. Relatively little is known about how disasters affect businesses, but the answers are important for helping local economies prepare for future disasters.

This article explores local firms' responses to one of the largest natural disasters in recent history: Hurricane Harvey, which struck Southeast Texas in 2017. We pursue two related questions. First, to what extent did Harvey cause firms financial distress? While some distress is expected, our goal is to quantify the *extent* of financial distress for firms in the affected area. Second, how did firms finance recovery from Harvey? We assess the use of dedicated disaster financing tools such as insurance and SBA disaster recovery loans, alongside a broader set of recovery financing options, including private loans, firms' cash flows, and friends and family resources. To answer these questions, we analyze the credit report data of 8,218 firms and conduct a survey of 273 local firms.

To what extent did Harvey cause firms financial distress? We measure financial distress using loan impairments on firms' credit reports. Impairments are consequential. They reflect an inability to meet contractual obligations and may increase future borrowing costs, reduce credit access, and limit other agreements (e.g., supply chain partnerships, leases).

We examine the relationship between flood depth and credit impairment in treatment-intensity, difference-in-differences regressions. In addition to flooded firms, our treatment group also includes firms in the disaster area who were not flooded but potentially affected by spillovers (e.g., customer and employee disruptions). Firms outside the affected area, both in Texas and throughout the U.S., comprise the control group, allowing a comprehensive assessment of Harvey's effects on financial distress.

We find a significant increase in delinquencies among firms flooded during Harvey. On average, Harvey caused a 9.7 percentage point (pp) increase in delinquent loan balances—doubling the pre-Harvey level—for firms in the most flooded areas (flood depths exceeding 2 feet). We observe this effect only for short- and medium-term delinquencies (<90 days); we do not find a significant effect on the most serious credit outcomes such as bankruptcy. This pattern may reflect businesses' substantial efforts to fulfill their debts. Delinquencies also increased by 3 pp among nonflooded local firms, suggesting spillover effects impacting nearby firms' cash flows.

Consistent with the internal capital markets literature (e.g., Campello (2002), Giroud and Mueller (2019)), we find that subsidiary firms exhibit less financial distress than independent firms at commensurate levels of flooding. We replicate our loan impairment analyses (which use a sample of independent businesses) using a sample of subsidiary businesses with distinct credit reports from their parent companies. We find that subsidiary businesses do *not* become delinquent on their loans. Additionally, we analyze subsamples of firms based on their pre-Harvey credit scores; firms with low credit scores experienced larger impairments due to Harvey.

Our survey data reveal specific losses caused by Harvey and the ensuing financial challenges. Harvey caused property damage to 39% of respondents.

Nearly 90% reported revenue losses including from utility outages, employee disruptions, and reduced customer demand. 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 recovery from Harvey? Understanding how firms funded recovery offers insights into the mechanisms linking flooding and financial distress. While insurance and credit are key tools for managing an infrequent, severe event like Harvey, financing constraints may limit firms' use of these tools (e.g., Rampini and Viswanathan (2010)). Constrained firms may dedicate their limited financing to production and expansion, allocating fewer resources to insurance and leaving insufficient financial flexibility for a rainy day (Giroud and Mueller (2017)). In turn, insufficient formal risk financing may force businesses into costly strategies that delay or prevent recovery.

Our survey shows that insurance played a very small role in firms' recovery, with only 15% using it to finance losses from Harvey. Many firms were uninsured against flood and wind damages. Over 60% of firms with flood damages did not have flood insurance. Firms who were struggling before the storm (e.g., those who were not profitable) were especially unlikely to be insured. Even among insured firms, about half of those with property damage did not receive a claim payment at all, and 42% of those who did reported that the payment was lower than expected. Firms *typically* did not report explicit contractual nonperformance (e.g., losses were on uninsured property or did not exceed the deductible) but rather a disconnect between their expectations and contractual terms.

Given the limited use of insurance, we might expect credit to play a central role in funding repairs. In addition to private sector loans, affected firms can apply for disaster assistance loans from the Small Business Administration (SBA), which have a low interest rate (between 3 and 7% for Harvey) and are intended to alleviate credit constraints for recovering firms (SBA (2023)).[1] Surprisingly, only a quarter of survey respondents used any form of credit to finance recovery, with fewer than 5% of firms using SBA disaster loans.

Half of surveyed businesses needing funds never applied for a loan. We asked firms who did not apply for an SBA disaster loan why they had not. The primary reasons included a reluctance to take on additional debt (39% of firms) and concerns about not being approved (14%). Other firms cited various frictions that impeded applying (e.g., lack of awareness or perceived paperwork burden). Concerns about additional debt align with the literature on debt overhang (e.g., Giroud and Mueller (2017), Fahlenbrach, Rageth, and Stulz (2021)) that existing obligations may limit a business's capacity for new borrowing. Revenue disruptions post-disaster might help explain these concerns, as businesses may have wanted to reduce their commitments in anticipation of reduced sales.

Beyond firms' reluctance to borrow post-Harvey, we also find evidence of supply-driven credit constraints: Half of surveyed firms who applied for credit from private lenders were denied. While the SBA applies less stringent underwriting

[1]SBA loans are the only federal assistance offered directly to firms. To minimize the cost to taxpayers, the SBA underwrites disaster loans using business cash flows and the owner's credit score. Disaster loans are not reported to credit agencies unless the borrower defaults.

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standards than private lenders, roughly two-thirds of disaster assistance loan applicants were denied.[2] Our findings on both SBA disaster credit demand and supply highlight the limited reach of federal disaster loans as a one-size-fits-all policy solution for affected businesses.

Instead of using credit and insurance, firms frequently turned to informal financing to fund recovery. *Half* of surveyed firms used informal financing from friends and family. Firms often want to avoid such financing as it can have long-term consequences, leading them to take on lower-risk, lower-return projects (Lee and Persson (2016)). Thus, firms' reliance on informal financing following Harvey may exacerbate the cost of the disaster by reducing their profitability in the years ahead.

Our study adds to a growing literature on how climate risks affect firms (e.g., Giroud, Mueller, Stomper, and Westerkamp (2012), Collier, Haughwout, Kunreuther, and Michel-Kerjan (2020), Brown, Gustafson, and Ivanov (2021), Allen, Shan, and Shen (2022), Gallagher, Hartley, and Rohlin (2023), and Goulbourne, Neto, and Ross (2023)). For example, Basker and Miranda (2018) examine firms post-Katrina, finding that survival is less likely for smaller firms and credit-constrained firms.[3] We offer a unique contribution by tracing out the consequences of a severe climate event in unprecedented financial detail. Specifically, we show that businesses experienced widespread business disruptions and (less frequently) property damages. While firms were typically able to stave off bankruptcy, we find evidence of moderate distress in the form of credit delinquencies, suggesting that firms' strategies offered only partial protection for their hurricane exposures.

We provide new insights on how privately held firms manage a large, negative shock. Several papers use natural disasters to examine how shocks affect publicly traded firms (e.g., Barrot and Sauvagnat (2016), Dessaint and Matray (2017), and Giannetti and Yu (2021)), but research on private firms is more limited. Several recent studies examine how widespread events such as the COVID-19 pandemic (e.g., Kim, Parker, and Schoar (2020), Bartlett and Morse (2021), and Alekseev, Amer, Gopal, Kuchler, Schneider, Stroebel, and Wernerfelt (2023)) and economic downturns (e.g., Chodorow-Reich (2013)) affect small and medium businesses. In contrast to these systemic risks, firms can purchase insurance to manage hurricane risk. The surprisingly small role of insurance in funding recovery—and the disappointing performance of contracts in place—aligns with a larger literature on the importance of trust in insurance markets (Gennaioli, La Porta, Lopez-de Silanes, and Shleifer (2022), Armantier, Foncel, and Treich (2023)). Even a small risk of nonperformance has been shown to significantly decrease insurance demand (e.g., Wakker, Thaler, and Tversky (1997), Zimmer, Schade, and Gründl (2009)). We find that firms frequently adopted recovery practices, such as delaying debt payments and using informal financing, that address immediate financial needs but may be costly in the long term.

[2]This higher denial rate among SBA applicants could reflect that, relative to private loans, more low-credit-quality firms applied for SBA loans.

[3]Several papers examine *households'* credit reports following hurricanes (Gallagher and Hartley (2017), Billings, Gallagher, and Ricketts (2022), and del Valle, Scharlemann, and Shore (2024)). del Valle et al. (2024) find that households minimize borrowing costs including by opening new credit cards at promotional rates and quickly paying down balances.

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We also contribute to research on financing frictions and their consequences (e.g., Campello, Graham, and Harvey (2010), Giroud and Mueller (2017), and Gilje, Loutskina, and Murphy (2020)). We examine firms in the aftermath of a severe event where financing constraints are likely to bind. We find evidence of such constraints: Firms were frequently rejected for loans, and unprofitable firms were less likely to be insured. These constraints seem to contribute to their distress following the shock. For example, flooding caused loan impairments for independent businesses, but not for businesses with parents. Our research also highlights that in addition to supply-side financing frictions such as credit rationing, firms often avoided taking on more debt. Given the growing costs of severe climate events, our findings suggest that current federal policy, which focuses on alleviating credit constraints, is insufficient to address a broader set of barriers limiting business recovery.

Section II provides background on Hurricane Harvey. We analyze and discuss our two data sources separately—the credit reports in Section III and the survey in Section IV. In Section V, we summarize our most important findings and discuss their implications.

II. Background

On Aug. 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, Wehner, Noy, and Rosier (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 Aug. 25 to Sept. 11 (USPS (2017)). At least 500 roads were closed due to flooding and damage, and 118 were still closed after 2 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 article. The only form of federal assistance offered to businesses is disaster recovery loans from the SBA. Small businesses can borrow up to $2 million from this program to repair damaged property and/or offset revenue losses.

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

One year following Hurricane Harvey, the overall approval rate for Harvey-related SBA disaster loans was about 40% (GAO (2020)).[5]

III. Credit Report Analysis

A. Data and Summary Statistics

We analyze data from Experian credit reports. Credit bureaus such as Experian collect information on businesses from lenders and other companies providing financial contracts to the business (e.g., lessors, credit card companies, utility providers). Experian credit reports cover 99.9% of all U.S. businesses (Experian (2023)). Moreover, credit bureaus maintain records on a business even if it ceases to operate. Lenders are a key user of business credit reports and most of the information on the report pertains to loans (e.g., balances, timeliness of payments, new applications). We focus on these loan-related outcomes.

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 County Business Patterns database (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 metrics are provided on a quarterly or monthly basis for the 6 months prior to the report date. 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 main analyses on businesses with fewer than 500 employees and without parents out of concern that larger, multibusiness firms may have access to additional resources (e.g., internal capital markets) that make these firms distinct from the

[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 2 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 IV. Our Texas random sample of credit reports uses counties in those districts to facilitate comparisons between the credit report and survey analyses.

TABLE 1

Data Cleaning and Filtering: Main Samples

Table 1 outlines the process to clean and filter raw data to arrive at final sample for analysis.

Data Step	Remaining Firms
All Firms with Experian Credit Records	10,200
Drop if no 2017 credit record	9,989
Drop duplicate credit records	9,721
Drop if number of employees ≥ 500	9,594
Drop if has a parent (according to *ReferenceUSA*)	8,218
Full Sample	8,218
Drop if 2017 or 2018 total loan balances = $0	2,614
Active borrower sample	2,614

other businesses in our sample. These filters reduce the data for our credit report analysis to the "Full Sample" of 8,218 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 1 update in the past 3 months; our "Active Borrower Sample" thus ensures that we capture the most current changes in a firm's ongoing credit performance.[7]

1. Credit Variables

When evaluating financial distress, our primary outcome of interest in the credit report data is loan impairment (PCTIMPAIRED_{it}), which we measure as the share of total loan balances for firm i at time t that are not paid on time within the agreed terms.[8] We study two outcome variables to evaluate how Harvey affected credit use: a firm's total loan balance (BALANCE_{it}) and its number of new credit inquires (INQUIRIES_{it}). An inquiry occurs when a lender checks the credit record of a business that is applying for a new loan. In subsample analyses, we compare firms based on their credit score prior to Harvey. 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.

2. Flood Variables

Our treatment variable is flood depth at the firm's location. We geocode the primary business address of the firm as of June 2017 and match the coordinates to

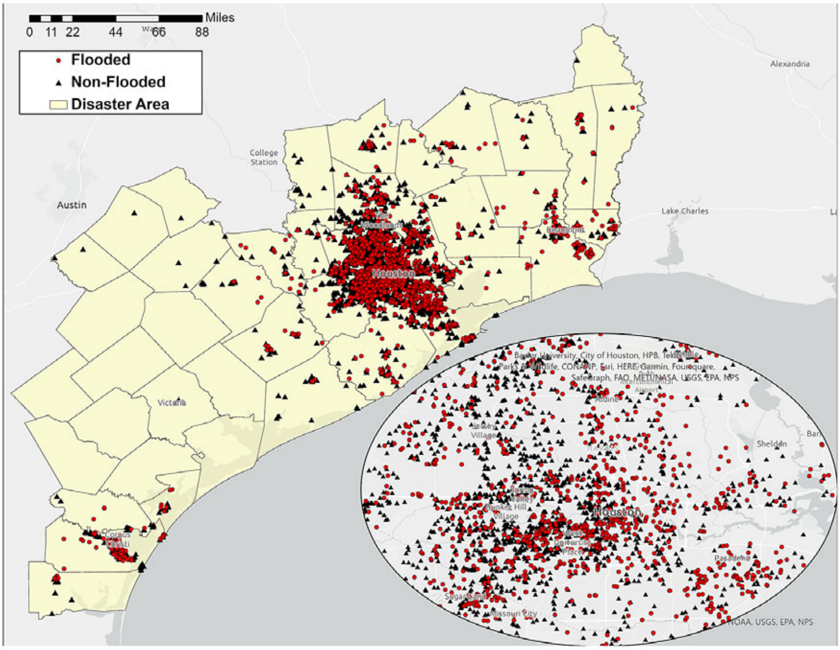
[7]In our conversations with them, Experian data managers indicated that credit report users focus on these "updated in the last 3 months" variables as it serves as an additional check on data quality. While lenders are servicing a loan, they regularly update the credit bureaus (typically monthly) regarding the evolving loan balances and any delinquencies. Thus, information on a loan for which no updates have been provided in the past 3 months is likely inaccurate (e.g., the balance may have been paid off or rolled into a new loan without the lender reporting this). As a robustness check for the analyses of impairments, we also examine samples including firms with zero balances in 2017 and/or 2018, setting impairments as zeros for these periods.

[8]This measure treats all overdue payments as the same, regardless of how long the payment has been delinquent. We also disaggregate this measure by length of delinquency and discuss those findings below (Section III.C.1).

FIGURE 1

Studied Firms in Disaster Area: Flooded Versus Nonflooded

Figure 1 is a map of flooded and non-flooded firms in counties included in Major Disaster Declaration DR-4332-TX.



FEMA's estimated Harvey-related flood depth at that address (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. Figure 1 presents the flooding distribution (flooded vs. nonflooded) of firms in the disaster area from our random sample, based on the FEMA flood depth data. About 36% 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 divide flooded firms into two groups based on the flood depth at their location. The LOWFLOOD group includes firms in areas with below-median flooding (≤ 2.05 feet). The HIGHFLOOD group includes firms in areas with above-median flooding (> 2.05 feet).[9] We also investigate effects using 2 other specifications: logged flood depth (ln(FLOODDEPTH)) and an indicator for any flooding (I(FLOODED)).

As a robustness check, we employ a second measure of flooding, I(FLOODED_REMOTE) (FEMA (2017a)). This measure is binary (flooded vs. nonflooded) and uses Synthetic Aperture RADAR and Multispectral Imagery sensors, collected by satellites, drones, and planes, to detect whether a particular location was flooded during Hurricane Harvey between Aug. 26 and Sept. 5, 2017.

[9]As a reference for the extent of damages caused by these levels of flooding, the U.S. Army Corps of Engineers estimates that *homes* with a flood depth of 2.05 feet from Harvey experienced damages equaling 32% of the property's value (Houston Chronicle (2018)).

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3. 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)). 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., median household income, population, education, race). We provide specifics on these control variables in Section III.B.

4. 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 discussion here; columns 2–5 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 8,218 firms. Among these firms, the mean and median number of

TABLE 2

Summary Statistics

In Table 2, the values in the first, second, and third rows under each variable are means, [medians], and (standard deviations), respectively. In columns 6–7, we divide the sample at the median based on the firm's pre-Harvey Experian Intelliscore. Higher credit scores indicate a greater repayment ability.

			Inside Disaster Area			Ex Ante Credit Score	
	Total	Outside Disaster Area	No Flood	Low Flood ≤ 2.05 Ft	High Flood > 2.05 Ft	High	Low
Variable	1	2	3	4	5	6	7
Panel A. Full Sample							
No. of firms	8,218	3,052	3,306	930	930	4,004	4,114
EMPLOYEES	9.52	10.05	9.07	8.98	9.87	11.02	8.28
	[3]	[3]	[3]	[3]	[3]	[4]	[3]
	(27.71)	(30.69)	(24.15)	(29.88)	(27.02)	(30.25)	(25.25)
YEARSINFILE	16.02	16.49	15.73	15.62	15.91	18.87	13.51
	[14]	[15]	[14]	[14]	[14]	[18]	[11]
	(10.64)	(10.84)	(10.51)	(10.45)	(10.59)	(10.44)	(10.10)
INTELLISCORE	47.49	48.18	47.31	46.30	47.12	69.31	26.21
	[43]	[44]	[43]	[41]	[41]	[68]	[27]
	(25.89)	(26.11)	(25.74)	(25.58)	(25.99)	(17.47)	(10.47)
BALANCE ($000)	25.67	32.71	24.18	17.55	15.96	30.02	22.06
	[0]	[0]	[0]	[0]	[0]	[0.1]	[0]
	(349.86)	(500.52)	(226.47)	(233.56)	(150.16)	(297.92)	(397.63)
INQUIRY (H1 2017)	0.33	0.37	0.32	0.29	0.22	0.37	0.29
	[0]	[0]	[0]	[0]	[0]	[0]	[0]
	(1.28)	(1.52)	(1.21)	(1.04)	(0.79)	(1.30)	(1.28)
Panel B. Active Borrower Sample							
No. of firms	2,614	981	1,044	295	294	1,799	815
EMPLOYEES	16.44	17.50	15.39	16.33	16.74	15.42	18.69
	[5]	[5]	[5]	[5]	[5]	[5]	[5]
	(42.15)	(46.43)	(36.96)	(46.44)	(39.92)	(40.05)	(46.39)
YEARSINFILE	22.58	23.85	21.94	21.02	22.17	22.79	22.10
	[23]	[24]	[22]	[21]	[23]	[24]	[22]
	(10.41)	(10.38)	(10.22)	(10.67)	(10.51)	(10.15)	(10.95)
INTELLISCORE	56.91	56.60	56.79	56.99	58.27	73.32	20.50
	[63]	[63]	[63.5]	[64]	[63]	[73]	[18]
	(28.18)	(28.67)	(27.80)	(28.17)	(27.94)	(14.75)	(12.17)
PCTIMPAIRED	0.15	0.17	0.14	0.14	0.10	0.05	0.36
	[0]	[0]	[0]	[0]	[0]	[0]	[0.24]
	(0.28)	(0.30)	(0.28)	(0.28)	(0.24)	(0.15)	(0.37)

employees are 10 and 3, respectively.[10] On average, these firms had 16 years of credit history in 2017. Their average loan balances totaled $25,670 with a median value of $0—over 60% of the full sample had no loan balances before Harvey. Their average number of credit inquires in the first 6 months of 2017 was 0.33. That is, for every 3 firms in our full sample, we observe one credit inquiry made by a firm in the first half of the year. The lower panel of Table 2 summarizes credit for the active borrower sample of 2614 firms. These firms had average loan balances of $77,890, with 15% of loan balances not paid on time before Harvey.

In our analysis, we are interested in how firms responded to Harvey differently according to their existing financial constraints. We do so by splitting our sample based on a firm's pre-Harvey "Intelliscore" index of credit quality. The index, ranging between 1 and 100, is created by Experian with higher scores indicating greater repayment ability (Experian (2013)). We define a firm's credit score as "high" if they have an above-median Intelliscore (>43), and "low" otherwise.[11] Columns 6 and 7 present descriptive statistics of the two groups. On average, low-credit-score firms borrowed less and made fewer credit inquiries than high-credit-score firms. Among active borrowers, those with low credit scores also had more impairments leading up to Harvey. Of their total balances, 36% were not paid on time (vs. 5% for low-credit-risk borrowers).

B. Empirical Methodology

To examine how flooding from Hurricane Harvey affected firms' credit impairments and inquiries, we use difference-in-differences estimations that impose treatments at increasing flood depths. Specifically, we estimate

$$
\begin{aligned}
(1)\qquad Y_{it} = {} & \beta_0 + \beta_1 \mathrm{I}_t(\mathrm{POSTHARVEY}) \times \mathrm{I}_i(\mathrm{NOFLOOD}) \\
& + \beta_2 \mathrm{I}_t(\mathrm{POSTHARVEY}) \times \mathrm{I}_i(\mathrm{LOWFLOOD}) \\
& + \beta_3 \mathrm{I}_t(\mathrm{POSTHARVEY}) \times \mathrm{I}_i(\mathrm{HIGHFLOOD}) \\
& + \theta \mathrm{I}_t(\mathrm{POSTHARVEY}) \times X_i + \mathrm{FE}_i + \mathrm{FE}_t + \varepsilon_{it},
\end{aligned}
$$

where i indexes firms and t indexes time, Y_{it} is a general term for the credit outcome of interest, and $\mathrm{I}_t(\mathrm{POSTHARVEY})$ is an indicator for post-Harvey periods. For our flood depth treatment variables, we use a set of indicators for whether a firm was located in one of four groups at the time of Hurricane Harvey: i) outside the disaster area (the omitted reference group), ii) in the disaster area but not flooded ("I(NOFLOOD)"), iii) in the below-median flood depth group ("I(LOWFLOOD)"), and iv) in the above-median flood depth group ("I(HIGHFLOOD)"). 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,

[10]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 (vs. 62% in the County Business Patterns Data) and 91% have fewer than 20 employees (vs. 89, U.S. Census Bureau (2017a)).

[11]Eleven firms (including 4 active borrowers) have a missing Intelliscore due to bankruptcy declarations in the 24 months prior to Harvey; we categorize them as having low credit scores. Hundred firms (none are active borrowers) have a missing Intelliscore due to a lack of information to generate a score; we drop them from the credit score subsample analyses.

employee disruptions, etc.). The treatment effects in equation (1) are captured by β_1 to β_3.[12] We also investigate several alternative specifications of flooding as treatment variables (e.g., logged flood depth). Our treatment variable of flood depth serves as a proxy for the overall severity of the event at a specific location. More severe flooding causes greater property damage, but also may interrupt business operations, damage infrastructure and create challenges for local consumers. Our analysis, therefore, captures the aggregate causal effect of the storm rather than property-related flood damages in isolation.

We interact a set of pre-Harvey control variables X_i with the post-Harvey indicator as a way of controlling for nonflood 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 a 2-digit SIC code), and ZIP-level demographic information (logged median household 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).

The credit reports provide monthly loan balances for the 6 months prior to the report date. To take advantage of this more granular measure and examine how balances evolve over time, we implement an event study analogue of equation (1), which replaces $\mathrm{I}_t(\mathrm{POSTHARVEY})$ with a set of indicators $\mathrm{I}_t(\mathrm{TIME})$ for each time period. The last observation before Harvey, in June 2017, serves as the reference period.[13]

The regression in equation (1) estimates a causal effect of flooding on credit outcomes under the parallel trends assumption—that the control and treatment groups would respond comparably had they both been affected in the same way by Harvey. We examine pre-event trends in our outcomes of interest at the firm level (e.g., loan balances, inquiries) for the treatment and control groups using the event study model. This analysis provides general support for the parallel trends assumption, as none of the pre-Harvey coefficients are significantly different from zero (Figure A.7 in the Supplementary Material). Additionally, we examine aggregate business statistics at the county level (e.g., establishment count, firm entry, firm exit, etc.) and conduct 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

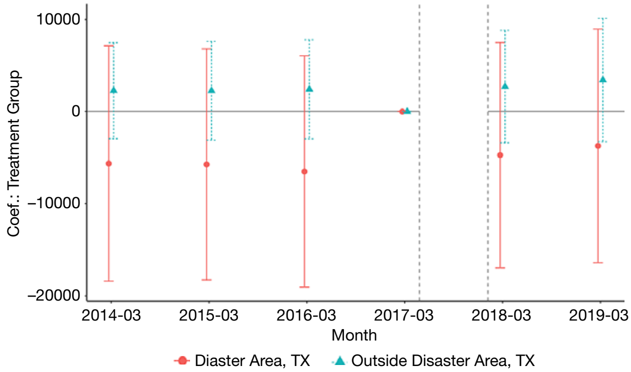
[12]The model estimates the intent-to-treat (ITT) effect, rather than the average treatment effect on the treated, due to imprecision in measuring flooding. Billings et al. (2022) use Harvey flooding to estimate ITT effects on households' credit outcomes. We can more precisely estimate flooding as we 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, and so forth. This measurement error will partially attenuate our estimates relative to true average treatment effects.

[13]The data also include quarterly information on credit inquiries. For simplicity in presenting the results, we examine inquiries in differences-in-differences estimations following equation (1). However, we use the quarterly data on inquiries to explore potential pre-trends and show the results in the Supplementary Material, which we describe below.

FIGURE 2

Number of Establishments at County Level

In Figure 2, the reference group is counties outside of Texas. The dotted vertical lines mark the time when Harvey occurred. Annual data from Business Dynamics Statistics and Nonemployer Statistics of the U.S. Census Bureau ((2018a), (2018b)) are a snapshot of business statistics in the week of Mar. 12 for each year. The data include establishments of firms with fewer than 500 employees.



differ from the national trend (see Table A.10 in the Supplementary Material for additional outcomes).

As additional support toward this causal interpretation, we believe that given model controls, treatment assignment can be viewed as plausibly random with respect to the considered credit outcomes. 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.

There are 2 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 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.[14] The second consideration is how our results generalize to other severe climate events. For reference, we also examine aggregate business statistics for 2 other large urban hurricanes, Hurricane Sandy and Hurricane Katrina in the Supplementary Material. The 1-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, and so forth. These comparisons do not guarantee generalizability, but do align with

[14]Lenders maintain credit records for several years after a firm closes. For example, consider a firm who closes with unpaid loans. Lenders to that firm will continue to report as those loans become more and more delinquent over time. Severe impairments such as legal filings remain on the firm's report for 7 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.

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previous findings indicating that Harvey appears similar to other large-scale hurricanes (e.g., Billings, Gallagher, and Ricketts (2023)).

C. Results

This section describes the effects of flooding on 3 credit outcomes: impairments, inquiries, and balances. In Section III.C.1, we examine overall impairments for our sample of local businesses who actively borrow. We extend this analysis to more deeply examine the role of financial constraints in Section III.C.2. We do so by analyzing impairments for low- versus high-credit-risk businesses and impairments for businesses *with* parents (which likely face fewer constraints than the businesses *without* parents in our first analysis). In Section III.C.3, we report our difference-in-differences regression of credit inquiries and event study analysis of loan balances, which also include some additional focus on heterogeneity across firms (e.g., ex ante credit use).

1. Impairment

We evaluate whether Harvey caused firms to miss their financial obligations by examining the share of loan balances that are past due ("PctImpaired"). Table 3 presents the results of estimating equation (1) for the active borrower sample defined in Section III.A.[15] We begin with a parsimonious specification (without any controls) in column 1 and add fixed effects and controls stepwise across the columns. Our preferred model is column 5, which includes firm controls (age, size, industry, and flood zone designation), ZIP code controls (median household income, population, etc.), and firm and year fixed effects. As shown in equation (1), we interact controls with a post-Harvey indicator to allow for the possibility that Harvey differentially affected certain populations. 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 causes a statistically significant increase 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 high flooding area, Harvey caused 9.7% of their total balances to become impaired 10 months after the disaster. Before Harvey, 10% of their loan balances were impaired on average (see the bottom row of column 5 in Table 2), so this effect represents a 97% increase over the pre-Harvey level for these firms. The estimated regression coefficient provides the average effect within the high flood group; however, there is substantial heterogeneity in impairment among firms in the most flooded area. About one-third of

[15]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 delinquent. As robustness tests, we conduct the same analysis and i) include the 477 firms who had positive 2017 total balances but zero 2018 total balances and ii) 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 Table A.11 in the Supplementary Material).

TABLE 3

Share of Balances That Are Impaired, Active Borrower Sample

In Table 3, the 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 ($PCTIMPAIRED_{it}$). The omitted reference group is firms located in counties outside the disaster area (both inside and outside of Texas). 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. Regressions report robust standard errors clustered by county. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	1	2	3	4	5	6	7	8
I(POSTHARVEY) ×								
I(NOFLOOD)	0.031***	0.032***	0.031***	0.027**	0.040***	0.040***	0.029***	0.048***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.014)	(0.014)	(0.011)	(0.015)
I(LOWFLOOD)	0.039***	0.056***	0.039***	0.033**	0.046***			
	(0.013)	(0.015)	(0.013)	(0.014)	(0.017)			
I(HIGHFLOOD)	0.090***	0.070***	0.090***	0.084***	0.097***			
	(0.014)	(0.019)	(0.014)	(0.015)	(0.019)			
I(FLOODED)						0.071***		
						(0.017)		
ln(FLOODDEPTH)							0.066***	
							(0.016)	
I(FLOODED_REMOTE)								0.073***
								(0.020)
I(TX)					−0.019	−0.019	−0.009	−0.019
					(0.017)	(0.017)	(0.014)	(0.017)
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
Adj. R^2	0.002	0.184	0.583	0.581	0.581	0.580	0.582	0.580

these firms had any increase in impairment, and approximately 9% of the firms had over half of their loan balances become impaired.[16]

Firms in the disaster area, but who did not experience flooding at their location, had 4.0% of their total balances move into impairment. Given the impact of Harvey on flooded firms, households, and infrastructure, it is likely that this increase in impairment for nonflooded firms is due to spillover effects from flooded areas (e.g., those firms may have been unable to repay their lenders because of lost revenue from customer disruptions).

The results are qualitatively similar throughout all specifications in columns 1–5. Inclusion of firm, industry, and ZIP code controls does not substantially change the estimated effects of flooding. Flood risk zone designations may help firms recognize their exposure and motivate them to prepare, yet controlling for the flood zone of firms in the disaster area also does not change our results.

Similarly, we observe positive and significant effects using 2 alternative specifications of flooding based on our flood depth data: an indicator for whether the

[16]In Table A.12 in the Supplementary Material, we run a set of robustness tests by restricting the treated firms inside Harvey disaster area to those in Harris County (where about 60% of treated firms were located), outside Harris County, in inland counties, in coastal counties, in high-income tracts, and in low-income tracts. The results are qualitatively similar across these specifications.

firm experienced any flooding in column 6, and the logged continuous flood depth in column 7.[17] 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.[18]

We further explore how the flooding effects on loan impairment vary by business industry in Table A.13 in the Supplementary Material. We find that the significant effects of flooding are concentrated within businesses that serve local customers (vs. businesses whose goods are traded and sold in other locations). In areas of severe flooding, both business-to-business (B2B) and business-to-consumer (B2C) firms had significant increases in loan impairment.

In Table A.14 in the Supplementary Material, we decompose impairment by length of delinquency (i.e., 1–30 days delinquent, 31–60 days delinquent, etc.) and evaluate more severe credit outcomes, including collections and legal filings (i.e., tax liens, judgments, and bankruptcies) in the last 12 months. We observe the largest effect from flooding on the shortest-term delinquencies (1–30 days delinquent) and a smaller but also significant effect on 61–90 day delinquencies. The longest delinquency level (over 90 days) and severe credit outcomes are not significantly affected. We also examine the *number* of reported loans (vs. the balances examined here) and similarly find that flooding increased loan impairment, concentrated in delinquencies of 60 days or less (Table A.15 in the Supplementary Material).

Taken together, the results show a meaningful decline in firms' loan performance due to Hurricane Harvey. While we do not find that flooding led to the most severe credit outcomes, these 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 new collections or legal filings in 2018). It is also possible 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, Taubman, Wright, Bernstein, Gruber, Newhouse, Allen, Baicker, and Group (2012)). Our findings motivate future research to examine credit outcomes over longer time horizons.

2. Impairment: Variation in Financial Constraints

In this section, we investigate whether the effect of Harvey-related flooding on loan impairment varies based on a firm's existing financial constraints. We capture financial constraints using two proxies: a firm's pre-Harvey credit score and whether a business is a subsidiary of a larger parent company. Because a firm's credit score and its status as a subsidiary may correlate with other factors, these analyses point toward potential mechanisms that may explain our results but do not meet the same causal standards as our main findings in the previous section.

[17]When using logged flood depth, we recode the cases in which the flood depth is 0 as ln(FLOODDEPTH) = 0 and identify these firms with the regression dummy, "I(NOFLOOD)."

[18]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.

TABLE 4

Share of Balances That Are Impaired, Varying Financial Constraints

Table 4 presents difference-in-differences estimates of flooding effects on loan impairments (PCTIMIPAIRED$_{it}$). The omitted reference group is firms located in counties outside the disaster area (both inside and outside of Texas). Column 1 uses our baseline active borrower sample of independent firms (without parents). In columns 2 and 3, we divide the sample at the median based on a firm's pre-Harvey credit score into high-credit-score and low-credit-score firms, respectively. The sample in columns 5–7 consists of actively borrowing subsidiary firms (with parents). In column 6, we apply propensity score weighting using a gradient boosting decision tree algorithm. In columns 4 and 7, we compare subsidiary and independent firms with at least 10 employees (greater than the overall mean of 9.5 employees). Models include firm fixed effects, year fixed effects, and control variables. Regressions report robust standard errors clustered by county. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Independent Firms				Subsidiary Firms		
	1	2	3	4	5	6	7
I(POSTHARVEY) ×							
I(NOFLOOD)	0.040***	0.035**	0.045	0.013	−0.028	−0.027	−0.076
	(0.014)	(0.015)	(0.034)	(0.023)	(0.034)	(0.034)	(0.064)
I(LOWFLOOD)	0.046***	0.022	0.084**	−0.004	−0.039	−0.012	−0.006
	(0.017)	(0.015)	(0.040)	(0.025)	(0.038)	(0.041)	(0.063)
I(HIGHFLOOD)	0.097***	0.090***	0.100***	0.109***	0.016	0.020	−0.181***
	(0.019)	(0.022)	(0.036)	(0.026)	(0.040)	(0.041)	(0.065)
I(TX)	−0.019	−0.017	−0.028	−0.024	0.044	0.042	0.069
	(0.017)	(0.018)	(0.037)	(0.030)	(0.034)	(0.035)	(0.065)
Credit score	All	High	Low	All	All	All	All
No. of employees	All	All	All	≥ 10	All	All	≥ 10
Propensity score weighted	No	No	No	No	No	Yes	No
Year 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 firms	2,614	1,799	815	804	488	488	165
Firm-year obs.	5,228	3,598	1,630	1,608	976	976	330
Adj. R^2	0.581	0.269	0.625	0.559	0.448	0.441	0.592

We expect businesses with low pre-Harvey credit scores (i.e., high credit risks) to be more financially constrained and, thus, experience more financial distress following the event. Billings et al. (2022) examine consumer credit outcomes following Harvey and find that adverse effects such as delinquencies were concentrated in households with low credit scores. Column 1 of Table 4 repeats for reference our preferred model for the active borrower sample (independent firms without parents, already shown in column 5 of Table 3). In columns 2 and 3 respectively, we split this sample into high- and low-credit-score groups based on the firm's Intelliscore prior to Harvey.[19] The difference in impairments is prominent for lower levels of flooding (<2 feet): High-credit-score firms were able to meet their obligations, but low-credit-score firms fell behind on an additional 8% of their total debts. In post-estimation tests, we find that this difference is statistically significant ($p < 0.01$). For severe flooding (> 2 feet), loan impairment increases for both groups to a similar degree (0.09 vs. 0.10). One interpretation of this effect is that the consequences of severe flooding are so substantial that they overwhelm even high-credit-score borrowers.

[19]Our threshold for "high" versus "low" credit scores is based on the median credit score of the full sample as of June 2017. Because a firm's credit score affects its access to credit, this analysis of active borrowers includes more firms with high credit scores ($n = 1{,}799$, in column 2) than firms with low credit scores ($n = 815$, in column 3).

In columns 5–7, we investigate the effects of flooding on loan impairments for small businesses *with* parents. These businesses are subsidiaries in multibusiness firms, according to *ReferenceUSA*, and have a distinct credit report from the parent company. Compared to independent businesses, we expect that subsidiaries 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 may have access to internal capital markets (e.g., Campello (2002), Giroud and Mueller (2019)).

Subsidiary firms are excluded from the baseline sample of independent businesses that we have used in the analyses thus far. The sample of subsidiaries includes 1,376 firms, 488 of which are active borrowers. Compared to the baseline sample, these active borrowers are larger: The average business has 25 employees (vs. 16 in the baseline sample, see Table A.16 in the Supplementary Material for summary statistics). The industry composition also differs: 17% of these actively borrowing subsidiary firms are in finance, insurance, and real estate versus only 8% in the baseline sample.

In column 5, we report the estimation results using the set of subsidiary firms. In contrast to the baseline sample in column 1, we do not observe significant changes in the share of loan balances that are impaired for flooded firms with parents. These results suggest that subsidiary businesses are less likely to enter financial distress for a given level of flooding.

One potential concern is that the differences between columns 1 and 5 might be due to compositional differences (e.g., industry, size) between businesses with and without parents. While our specification in column 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 with a propensity score weighting approach (column 6), using a gradient boosting decision tree algorithm to improve predictive accuracy in the propensity estimates (Imbens and Wooldridge (2009)). We can directly compare firms with at least 10 employees between independent and subsidiary firms in columns 4 and 7.[20] The alternative estimations in columns 6 and 7 suggest similar results to column 5 in that flooding does not increase loan impairments for the subsidiary sample. For the relatively larger firms in column 7, we actually observe a decline in delinquencies for heavily flooded firms. While we are reticent to draw strong conclusions from a relatively small sample, a possible explanation for this decline is that internal capital flowing to heavily flooded subsidiaries is helping above and beyond disaster damages. Overall, the analyses in Table 4 compare firms based on likely financial constraints and show that distress is concentrated in firms with existing constraints.

3. Inquiries and Balances

Business credit reports also offer insights regarding firms' use of credit during the recovery process. In this section, we examine whether Harvey led firms to apply for credit and whether Harvey affected their debt balances. Unlike the analysis of impairments, which only examined borrowers who carried loan balances, we

[20]We chose this threshold because the mean employee count for the overall sample was 9.5. Our results remain qualitatively similar when using other employee size cutoffs.

TABLE 5

Number of Inquiries

Table 5 presents difference-in-differences estimates of flooding effects on inquiries. Dependent variable is the number of inquiries in the past 6 months ($INQUIRIES_{it}$). "Borrowers" are firms with positive balances as of Jan. 2017. "Nonborrowers" are firms with zero balances as of Jan. 2017. The omitted reference group is firms located in counties outside the disaster area (both inside and outside of Texas). Models include firm fixed effects, year fixed effects, and control variables. Regressions report robust standard errors clustered by county. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Borrowers			Nonborrowers		
	1	2	3	4	5	6
I(POSTHARVEY) ×						
I(NOFLOOD)	−0.082	−0.139	0.080	−0.003	0.035	−0.028*
	(0.106)	(0.120)	(0.220)	(0.023)	(0.043)	(0.016)
I(LOWFLOOD)	−0.038	−0.083	0.071	0.001	−0.036	0.030
	(0.115)	(0.134)	(0.199)	(0.026)	(0.044)	(0.028)
I(HIGHFLOOD)	0.285***	0.069	0.742***	0.009	−0.002	0.012
	(0.104)	(0.131)	(0.216)	(0.030)	(0.047)	(0.022)
I(TX)	0.114	0.179	−0.069	−0.007	−0.077	0.047*
	(0.133)	(0.175)	(0.219)	(0.028)	(0.052)	(0.025)
Pre-Harvey credit score	All	High	Low	All	High	Low
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	2,148	1,445	703	6,070	2,559	3,411
Firm-year obs.	4,296	2,890	1,406	12,140	5,118	6,822
Adj. R^2	0.638	0.588	0.686	0.270	0.357	0.188

extend our attention to the full sample of all 8,218 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 and loan balances by separating the sample into two groups. "Nonborrowers" are firms who had no existing debt as of Jan. 2017 and "borrowers" are those who did. We further divide nonborrower and borrower samples based on their pre-Harvey credit scores and investigate the role of financial constraints on their use of credit for recovery.

First, we examine the number of credit inquiries as a measure of a firm's demand for new credit. To the extent that Harvey-related flooding leads to additional expenses for the repair of flood damage, we would expect the need for funding such expenses to grow for firms that experienced severe flooding. Table 5 presents difference-in-differences estimation results using the number of inquiries in the past 6 months as the dependent variable. We find a significant increase in the demand for credit by firms with existing debt (column 1): borrowers in areas with high flooding increased their credit inquiries by 0.29 in the first half of 2018 due to Harvey. This effect represents a 30% increase over their pre-Harvey level in the first half of 2017. The development of inquiries for nonborrowers, on the other hand, does not seem to change after Harvey (column 4).

In the other columns of Table 5, we explore heterogeneity based on ex ante credit score. Compared to high-credit-score firms, we expect those with low credit scores to be more resource-constrained following Harvey and, thus, have a greater demand for new credit. Columns 2 and 3 show that the increase in inquiries among existing borrowers is driven by low-credit-score firms in the most flooded areas: On average, 3 out of 4 of these businesses made an additional credit inquiry because of Harvey, equivalent to a 58% increase relative to their pre-event level.

Next, we examine the effect of Harvey flooding on credit use, as measured by loan balances. Unlike credit inquiries, which are driven by firms' credit demand, changes in loan balances may reflect post-Harvey changes in both demand and supply. For firms who relied on credit to support day-to-day activities prior to Harvey (i.e., pre-event borrowers), changes in loan balances also may reflect adjustments to existing business operations.

Information on loan balances is provided on a monthly basis. Accordingly, we construct a balanced panel in which Feb. 2017 to June 2017 represent the pre-Harvey periods, a gap exists in the credit report data from July 2017 to Dec. 2017, and then Jan. 2018 to June 2018 represent the post-Harvey periods. We apply our event study version of equation (1) and estimate this model separately for borrowers and nonborrowers, and further divide each sample based on pre-Harvey credit scores.

We illustrate our event study results on high flood depth in Figure 3. Here, we observe a divergence between existing borrowers and nonborrowers. High flooding from Harvey caused a *decrease* in loan balances for existing borrowers (Graph A). Balance reductions are significant among high-credit-score borrowers. For example, in Jan. 2018 (5 months following Harvey), borrowers with high credit scores decreased their monthly balances by 45% because of Harvey. As shown in Table 5, these businesses did not make additional credit inquiries following Harvey, suggesting that they may be voluntarily deleveraging by decreasing their obligations in response to reduced revenues following Harvey (e.g., operating with fewer staff or less inventory in the short term).[21]

In contrast to borrowers, nonborrowers started borrowing in the post-Harvey periods and total loan balances increased significantly for those in areas with high flooding (Graph B). Recall that these firms did not make additional inquiries post-Harvey, suggesting that they were using existing credit (e.g., already opened lines of credit or credit cards) to fulfill their needs. The balance increases are more pronounced for nonborrowers with high pre-event credit scores, an indication that existing constraints also may play a role.[22]

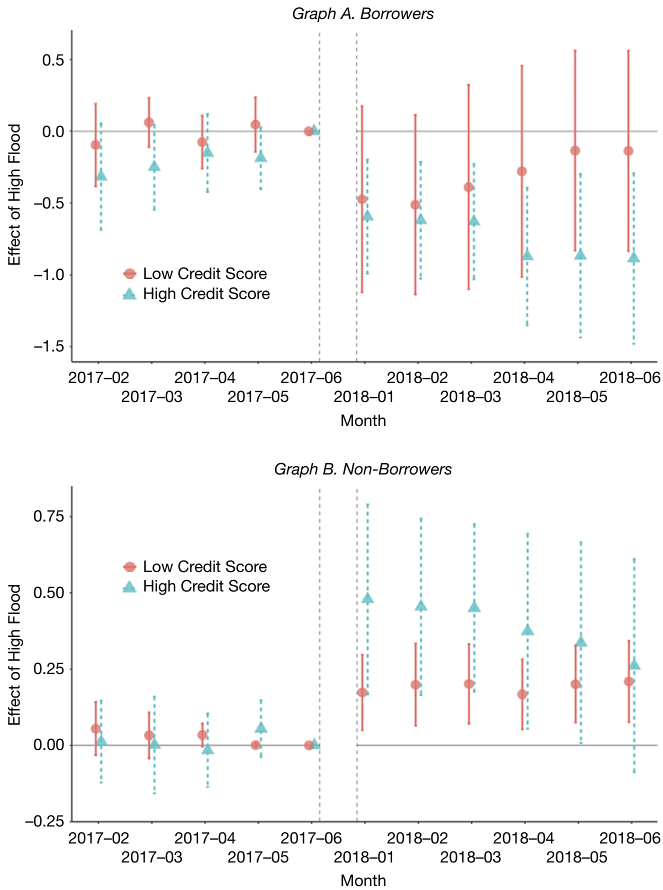
[21]Several recent studies document voluntary deleveraging by small businesses in response to a negative shock. For example, Wheat and Mac (2023) find that small businesses lowered revolving credit card balances following the COVID-19 pandemic to cut operating expenses when they saw a decrease in revenues. According to the 2020 Small Business Credit Survey from the Federal Reserve Bank (2020), small businesses faced with a (hypothetical) 2-month revenue loss would consider reducing salaries (37%), laying off employees (34%), deferring expenses (30%), and downsizing operations (30%).While SBA disaster loans are required to be spent on repair and recovery efforts (punishable by fines and even jail time), funds are fungible and it is possible that some of these firms were substituting existing debt into SBA disaster loans, considering that the balances fell significantly only among high-credit-score firms, who were more likely to receive approval from SBA. However, only a small proportion (less than 7%) of firms in our survey used SBA disaster loans to fund losses.

[22]To investigate whether the observed changes in loan balances are supply-driven, we examine the number of new accounts per inquiry (our proxy for successful inquiries) in Table A.17 in the Supplementary Material. We find no significant changes among flooded firms post-Harvey, regardless of ex ante borrowing or credit score. Thus, we do not find evidence that the likelihood of an inquiry being approved is significantly different for firms in the area affected by Harvey than for other firms.

FIGURE 3

Evolution of Monthly Loan Balances by Ex Ante Borrowing and Credit Quality

Graphs A and B of Figure 3 plot 95% confidence intervals of event study coefficients on I(HIGHFLOOD). Dependent variable is ln(BALANCE + 1). The coefficients capture the average change in loan balances relative to 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 balances. Harvey occurred during that period. We compare two groups: firms with positive balances as of Jan. 2017 ("borrowers") and those with zero balances at that date ("nonborrowers").



Our findings align with existing research on how Harvey affected households' finances. Billings et al. (2022) find that Harvey-related flooding increased measures of financial distress on consumers' credit reports, such as loan delinquencies. This distress was concentrated among households who were likely to be ex ante financially constrained: consumers with lower credit scores, those in lower income areas, and those who were less likely to have flood insurance. del Valle et al. (2024) find that better-off households found ways to minimize borrowing costs in the aftermath of the storm (e.g., by opening credit cards at promotional, zero-interest rates and paying balances down before the promotion expired). Thus, our results show that, like households, businesses faced financial distress following Harvey and existing constraints appear to limit their recovery funding options after the storm.

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In summary, the analyses of inquiries and balances shed light on the extent to which firms use credit to fund recovery. The results are consistent with debt overhang—firms without existing debt have the financial flexibility to borrow after the storm, while firms with existing debt obligations do not (Myers (1977), Giroud and Mueller (2017), and Fahlenbrach et al. (2021)). To better understand the circumstances surrounding the distress and credit use patterns in firms' credit reports, we turn to our survey of local firms.

IV. Business Recovery Survey

A. Overview

While the credit report data offer deep insights 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. First, we describe the ways in which Harvey affected the operations of our surveyed firms (Section IV.B). We then address our core research questions regarding how firms funded losses from the disaster (Section IV.C). In Section IV.D, we evaluate whether financially constrained firms were less likely to have risk management in place ex ante, as predicted by Rampini and Viswanathan (2010).[23]

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 e-mail their members with links to the online survey. We provide a detailed description of the distribution and design of the survey in the Supplementary Material. In total, we received 374 valid responses, 303 of which were complete.[24] 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 nonlocal business. This results in 273 responses for our survey data analysis—122 through the letter-writing campaign and 151 through business organizations.[25]

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

[23]In addition to our survey, other surveys have examined the experience of local businesses in the aftermath of major natural disasters, including Tierney (1997), Marshall, Niehm, Sydnor, and Schrank (2015), Lee (2021), and Liang, Ewing, Cardella, and Song (2023).

[24]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.

[25]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.

TABLE 6

Characteristics of Firms in the Survey Data and Experian Data

In Table 6, 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 2 digits of the firm's SIC code. Number of employees and firm age are self-reported for the survey sample.

ZIP Code Population	Survey Pct.	Experian Pct.	No. of Employees	Survey Pct.	Experian Pct.
0–5000	4.46	4.58	0–4	46.15	62.31
5000–20,000	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			

than 5 employees (46%), about a quarter had between 5 and 9 employees (25%), and only 6 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 5 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.

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 active borrowers in this survey population following the regression strategies outlined in Section III. 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 5.7 percentage points for surveyed firms in the most flooded areas, relative to nonflooded firms, and this result is significant at the 5% level (Table A.18 in the Supplementary Material reports the full results).

While our survey sample appears similar to our credit report sample, the standard limitations of surveys are important to note. Among other limitations, survey respondents participated voluntarily (potentially affecting the representativeness of the sample), responses are self-reported, and the sample size is relatively small. As a result, we treat this analysis of the survey as descriptive, helping clarify the results of the causal analysis that we conducted using business credit reports.

B. Harvey and Firms' Operations

How did Harvey affect firm operations? In Table 7, we list different types of losses and the proportion of respondents who experienced each (column 1).

TABLE 7

Losses, Disruptions, and Recovery

Column 1 in Table 7 is the proportion of surveyed firms that reported experiencing the loss denoted in the respective row. Both Recovered Pct. (column 2) and Mean % ΔEEs (column 3) 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 employees from June 30, 2017 (pre-Harvey) to June 30, 2018 (post-Harvey).

	Pct. of Respondents	Recovered Pct.	Mean % ΔEEs
	1	2	3
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

This column shows that nearly all firms (92%) had some type of loss. Approximately 39% of our surveyed firms reported property damage due to flooding and/or strong winds.[26] Disruptions were typically short—about a third of firms were closed for less than a week, and about three-quarters reopened within a month. More than 20%, however, were closed for longer periods of time. Businesses were interrupted most often because of employee disruptions, reduced operations (such as shorter hours or decreased production), and lower customer demand. Fewer firms experienced extended utility outages or disruptions to their suppliers.

To evaluate the lasting impact of these challenges, we compare firm recovery by the type of loss/interruption. In column 2, we report the proportion of firms that 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 larger effects for firms closed longer than 1 week and longer than 1 month. Compared to other interruptions, firms that experienced utility outages and supplier disruptions appear less likely to have fully recovered.

The outcomes in Table 7 provide details about the effects of Harvey that offer important context to understand the credit report analysis. For example, the delays

[26]Other than in coastal areas, Harvey was primarily a flood event. Among coastal counties, 46% of firms experienced wind damage, compared to 17% in noncoastal counties.

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in recovery may explain the credit impairments and inquiries in Section III. The survey results also illustrate specific business disruptions that affected both flooded and nonflooded 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.

C. 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: insurance for infrequent, but severe loss events such as hurricanes, borrowing for moderate losses, and reserves (such as liquid savings) for modest losses (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). A large proportion (48%) also relied on informal financing from personal resources.

Even though insurance is designed specifically for events like Harvey, only 15% of firms with financial needs used insurance payments to fund recovery. One reason for this low proportion is that many firms were uninsured, especially for flooding. About one-third of firms with wind damage lacked wind insurance, while nearly two-thirds of flooded firms did not have flood insurance. Business interruption insurance, which replaces lost revenue when a covered physical loss occurs, was also fairly rare; 22% of respondents had coverage in place.[27]

In Figure 5, we illustrate the insurance-related outcomes for firms with property damage. Businesses with insurance often did not receive claims payments—only about half of insured firms with physical damages received payment from their flood or wind insurer. We asked insured firms with property damage how insurance payments compared to their expectations; 22 of 53 respondents said payments were lower than they expected. In a follow-up question about the reason for a low payment, 23% chose the option that indicates potential nonperformance—that the "settlement was insufficient." Most of these respondents chose reasons that suggest a disconnect between consumer expectations and contract terms (e.g., cause of loss was excluded, damaged property was not insured, loss did not exceed their deductible). However, a few businesses described the insurer denying a claim that they believed should be paid (e.g, the insurer "alleged the covered loss was not covered"). While the potential of strategic claims denials by insurers is especially concerning, even cases in which the contract performed as written but the policyholder was unsatisfied are worrisome. A growing literature highlights the importance of trust in insurance contracting (Gennaioli et al. (2022), Armantier et al.

[27]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.

FIGURE 4

Recovery Funding Sources

Funding sources are reported in Figure 4 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.

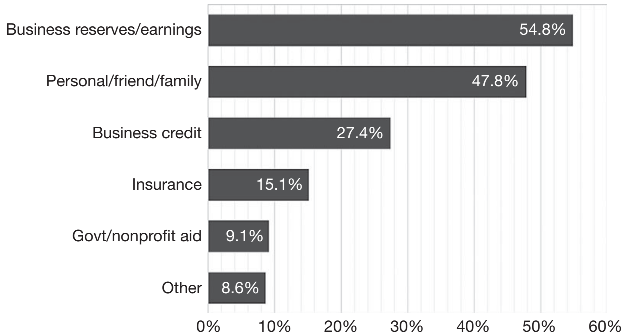
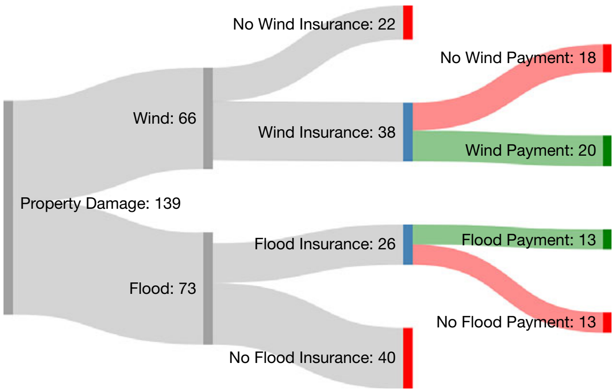


FIGURE 5

Property Damages and Insurance

The Sankey plot in Figure 5 illustrates the insurance-related outcomes for surveyed firms with property damage. Values are the number of respondents in each category. Wind and flood damages are illustrated separately for readability; 33 firms had damage from both wind and flood, while 40 firms had only flood damage and 33 firms had only wind damage.



(2023)), and these negative experiences may help explain low demand for insurance. Even a small risk of nonperformance can significantly decrease insurance demand (Wakker et al. (1997), Zimmer et al. (2009)).

About a quarter of firms with financial needs used business credit 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.[28]

[28]Interestingly, the approval rate from private lenders (e.g., banks) was about 50% (38 of 75 applicants), while the approval rate for SBA disaster assistance loans was 35% (17 of 49 applicants). This may

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TABLE 8

Reasons for Not Applying for SBA Disaster Recovery Loan

In Table 8, of the 186 firms with financial needs post-Harvey, 134 reported that they did not apply for an SBA disaster recovery loan. We asked these firms why they did not apply and received 100 responses. Several answered "Other" and provided a reason in an open-response text box. Where appropriate, we re-coded those answers into a given category based on the description provided.

Reason	Pct.
Unwilling to take on more debt	39.0
Not aware of SBA disaster loans	18.0
Unlikely to be approved	14.0
Too much paperwork	12.0
Did not want government assistance	7.0
Unattractive loan terms	6.0
Keep financials private	3.0
Other	1.0

One key form of credit is SBA disaster recovery loans, which are designed to provide funds to small businesses in the wake of a disaster such as Harvey. Of the 186 firms with financial needs, only 49 applied for such loans. We asked the remaining firms why they did not apply for SBA loans, receiving 100 responses. The most common response was that they were unwilling to take on more debt (39%). Another group did not apply because they felt unlikely to be approved (14%) which, combined with the 32 firms whose SBA loan applications were denied, highlights the compounding effect of financial constraints. The remaining reasons can be categorized as the result of other frictions. For example, 18% were not aware of SBA disaster loans and 12% did not apply because there was too much paperwork. Table 8 outlines the responses to this follow-up question.

More broadly, the small roles of credit and insurance in funding recovery indicate that formal, arm's-length risk financing structures were insufficient. As Figure 4 shows, nearly half 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.

D. Investigating the Role of Frictions

Thus far, our analysis of the survey data sheds light on Harvey's effects on local firms and their strategies for recovery. One open question is the extent to which firms' ex ante risk management—whether it had insurance, reserves, or available credit in place when Harvey occurred—is associated with existing financial constraints. Models of corporate risk management focus on the hedging strategies of publicly listed firms (e.g., Froot et al. (1993), Rampini and Viswanathan

reflect self-selection: Those applying for SBA loans may have done so because they anticipated that they would not be approved by a private bank.

(2010)), far removed from local firms' management of hurricane risk. Our survey offers an opportunity to explore the connection between frictions and risk management. These analyses exploit cross-sectional variation between respondents in regression, and we interpret these regressions as identifying *associations* rather than causal relationships.

We asked respondents about the firm's financial health just prior to Harvey; these questions provide a sense of the firm's financial constraints. Respondents indicated whether the firm was operating at a loss (11%), breakeven (22%), or at a profit (67%). Operating at breakeven or a loss poses financial constraints that are likely to be relevant for ex ante risk management decisions. For example, a firm that is operating at breakeven may decline insurance due to its relatively high opportunity cost.

We also asked firms about their ex ante risk management: flood insurance, wind insurance, business interruption insurance, emergency cash (e.g., a rainy day fund), and emergency credit (e.g., a business credit card for emergencies) that they had in place when Harvey occurred. Because both risk management and firm financial health may be correlated with other factors such as firm age, size, and industry, we control for such factors using regression.[29] Specifically, we regress ex ante risk management on the financial health factors described previously, controlling for firm demographics, prior loss experience, and industry. We estimate the following linear probability model:

$$(2)\quad \mathrm{P}_i(\mathrm{EXANTERM}) = \alpha + \gamma_1 \mathrm{I}_i(\mathrm{LOSS}) + \gamma_2 \mathrm{I}_i(\mathrm{BREAKEVEN}) + \theta X_i + \mathrm{FE}_j + \varepsilon_i,$$

for firm i in industry j. The dependent variables in equation (2) are indicators for whether a firm had flood insurance, wind insurance, business interruption insurance, emergency cash reserves, or emergency credit in place prior to Harvey. Our variables of interest are indicators for operating at a loss or breakeven pre-Harvey, with operating at a profit serving as the reference group. Controls in X_i include logged firm age, an indicator for firms established in 2017, the logged number of employees, an indicator for having no employees, an indicator for prior flood experience, an indicator for being located in a coastal county, and an indicator for firms recruited from our mail campaign (vs. through a business association). We also include industry fixed effects in FE_j. Table 9 reports the results of our estimations.

The regression results show that greater financial constraints are associated with less risk management. Firms operating at a loss were about 40% less likely than profitable firms to have flood or wind insurance or emergency cash reserves. Breakeven firms were better protected, but still were significantly less likely than profitable firms to have wind insurance, emergency cash, or emergency credit. Compared to profitable firms, both groups were similarly unlikely to have business interruption insurance. In summary, we find a negative association between a firm's ex ante constraints and its risk management that aligns with a larger literature connecting frictions and corporate risk management decisions (e.g., Rampini and Viswanathan (2010)).

[29]In addition to these controls, a variety of omitted variables may correlate with financial health and risk management (e.g., business acumen), motivating our description of the results as associations.

TABLE 9

Ex Ante Risk Management and Financial Constraints

In Table 9, dependent variables are dummies for the business having flood insurance, wind insurance, business interruption insurance, emergency cash reserves, or emergency credit, as noted in the table header. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Flood Insurance	Wind Insurance	Bus. Int. Insurance	Emergency Cash	Emergency Credit
	1	2	3	4	5
I(LOSS)	−0.340***	−0.413***	−0.130**	−0.428***	−0.057
	(0.069)	(0.089)	(0.054)	(0.092)	(0.095)
I(BREAKEVEN)	−0.075	−0.215***	−0.123**	−0.260***	−0.143**
	(0.074)	(0.074)	(0.056)	(0.082)	(0.071)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R^2	0.187	0.278	0.199	0.209	0.161
No. of obs.	232	216	240	252	258

V. Conclusion

The increasing frequency and severity of climate events imposes additional costs on firms. Risk management adds value by reducing the cost of risk, yet frictions may limit firms' use of efficient strategies. Our study offers new insights by tracing out the effects of a severe climate event 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 quantify the financial distress Hurricane Harvey caused for local firms. Credit delinquencies doubled for firms in the worst-flooded areas. We also observe spillover effects causing distress in neighboring areas that were not flooded. Surveyed firms often neglected formal recovery financing strategies (e.g., insurance and credit) that likely have the lowest costs. Instead, businesses commonly turned to informal financing, which may have long-term negative effects because it erodes limited liability protections. Surveyed firms struggled to recover from Harvey—nearly half of affected firms still had not recovered nearly a year later.

Our findings highlight the broad set of challenges local firms face in the wake of a disaster, revealing limitations in the existing set of risk management tools and public policies. Effective risk management involves organizing financing ex ante, such as buying insurance and limiting debt overhang. However, many firms had not taken these steps before the storm. Policy interventions could encourage ex ante preparation through mitigation subsidies or tax-preferred savings accounts. That said, federal flood insurance is already subsidized and few firms in our sample purchased it, raising questions about how businesses evaluate risk-related subsidies. Our findings also highlight coverage gaps in standard insurance policies. For example, many firms experienced revenue disruptions due to lower customer demand, which is not covered by insurance. Financial innovations such as parametric insurance offer potential as a cost-effective and transparent way to address such gaps. In sum, insurance market innovations and interventions that increase ex ante preparedness may help address the challenges that we document and are important topics for future research.

Supplementary material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109024000103.

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