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Alternative Finance after Natural Disasters

Konstantinos Baltas,[1] Franco Fiordelisi [1] and Davide S. Mare [1,2]
[1]Finance Group, Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, UK
[2]Finance and Private Sector Development (DECFP), World BankUniversity of Edinburgh Business School, 1818 H Street N.W., Washington, D.C., 20433, USA
Corresponding author email: franco.fiordelisi@essex.ac.uk

In this paper, we show that alternative finance (e.g. private equity, crowdfunding and venture capital) is a key source of funding for firms that are affected by natural disasters. Using data on a large sample of US companies from 2010 to 2019, we provide robust empirical evidence that private funding increases within 3 months after the occurrence of a natural disaster. Panel data analysis at state level shows that extreme events cause at least an average increase of funding from alternative finance by 47% relative to firms in non-affected states. We also find that size, reliance on physical assets and age improve access to alternative finance after adverse natural events. Our empirical evidence highlights the key role of private lenders in providing financial resources to affected firms after extreme exogenous events.

Introduction

Natural disasters present a broad range of economic, environmental, financial, human and social impacts, with potentially long-lasting, multigenerational effects. These sudden extreme events harm economic growth (Cavallo *et al.*, 2013; Strobl, 2011) and increase uncertainty and challenges for organizations (Doern, Williams and Vorley, 2019).

At the firm level, natural disasters result in a greater firm demand for funds and heightened credit constraints. There is greater demand for funds intended to restore damages caused by natural disasters, maintain business continuity, secure liquidity positions and develop new opportunities (Barth, Sun and Zhang, 2019; Brown, Gustafson and Ivanov, 2020; Koetter, Noth and Rehbein, 2020). Greater credit constraints occur because traditional sources of finance (especially bank loans) may not be available, since extreme natural events increase acute physical risks, which lead to a deterioration in firms' creditworthiness and ability to borrow from banks. Specifically, natural disasters result in physical asset disruption, which reduces the value of the collateral and weakens a firm's capability to obtain financing through mainstream sources.[1] This mechanism is well exemplified in the case of bank lending. Firms must make new investments to restore damaged physical assets, and thus banks register a sharp increase in new loan requests. At the same time, banks face a contemporary surge of deposit withdrawals, as affected individuals and firms must make up for the economic damage and an increase in their current expenses (Brei, Mohan and Strobl, 2019). Consequently, banks may have to draw on liquid

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[1]In this paper, we refer to mainstream finance or traditional lending as financing obtained through banks and other financial intermediaries and markets, such as insurance companies and capital markets.

assets and reduce lending in severely affected regions (Nguyen and Wilson, 2020).

A growing number of papers (Chavaz, 2016; Choudhary and Jain, 2017; Cortés and Strahan, 2017; Nguyen and Wilson, 2020; Schüwer, Lambert and Noth, 2019) have investigated whether bank lending increases or decreases after a natural disaster, reaching mixed evidence. The focus of all these papers is on bank lending reaction after natural disasters, but there is scant evidence of the ability of firms to raise funds after natural disasters through channels other than the traditional financial system, such as banks and capital markets, that do not rely on collateral to make financing decisions.

We fill this gap by answering the following question: do firms increase their funding from alternative funding sources after a natural disaster? Our paper addresses this question by showing whether funds provided by alternative funding sources (henceforth labelled 'alternative finance'[2]) increase after a natural disaster. This is an essential issue, given that extreme natural events engender the business continuity (and sometimes the survival) of affected firms and alternative finance sources may be the only available option. The fact that a natural disaster is an exogenous shock provides us with a quasi-natural experiment setting that enables us to compare changes in funds collected from alternative finance channels for companies that are 'treated' by a natural disaster (i.e. their physical assets have been damaged, which undermines their ability to provide collateral in traditional lending) and companies that are 'non-treated' by natural disasters (i.e. counterfactual evidence). We provide empirical evidence (both at the state and firm level) that natural disasters cause an increase in the amount raised through alternative funding within 3 months after the event, focusing on the United States between 2010 and 2019. Since extreme weather events have a differential impact depending on firm heterogeneity, we next investigate the role of firm characteristics and deal type in the provisioning of alternative finance after natural disasters. We show that financing through alternative sources after natural disasters increases for large-sized firms, firms relying on physical assets and start-up firms. Moreover, we provide evidence that debt financing is the preferred choice of firms in raising funds, whereas early-stage financing is negatively affected in the aftermath of an extreme weather event.

Our work contributes to two different strands of the literature. First, we contribute to the entrepreneurial finance literature (Cumming *et al.*, 2019; Wood and Wright, 2009) by shedding light on the provisioning of funds by investors after the occurrence of a natural disaster. Previous papers involved in crisis response management have examined either the responses of firms to natural disasters via business continuity management, including risk and disaster management (Herbane, Elliott and Swartz, 2010), or the corporate philanthropic responses to natural disasters and their subsequent reputational and financial benefits (Muller and Whiteman, 2009; Tilcsik and Marquis, 2013). However, little is known about whether firms hit by extreme weather events obtain more funds from alternative sources. Thus, our paper fills this void by providing novel empirical evidence on which firms increase their reliance on alternative finance at catastrophic times when they most need funds.

Second, we contribute to the literature that investigates firms' access to finance in the aftermath of crises (Doern, Williams and Vorley, 2019). Previous studies focused on traditional sources of funding, such as banks (Cortes and Strahan, 2017), insurance companies (Collier *et al.*, 2020; MacLaren *et al.*, 2017), grants (Gallagher, Hartley and Rohlin, 2020), trade credit (Casey and O'Toole, 2014), business loans (De Mel, McKenzie and Woodruff, 2013) and government transfers (Gallagher, Hartley and Rohlin, 2020). However, there is insufficient information regarding the role of private investors (alternative finance) on financing the recovery of firms after a catastrophic event. The empirical evidence suggests that in the aftermath of financial crises, alternative finance channels are a viable and elective source of funding, especially for small and medium-sized enterprises (Ardic, Mylenko and Saltane, 2011; Casey and O'Toole, 2014) and start-ups (Zhang *et al.*, 2015). Nevertheless, evidence is limited on the ability of firms to raise funds from alternative

[2]Alternative finance is intended here as all financial channels that have emerged outside of the traditional finance system, such as regulated banks and capital markets. Alternative finance activities include investments by private firms including angels (wealthy individuals), venture capital, private equity, crowdfunding and other forms of fintech (Allen, Gu and Jagtiani, 2021; Farag and Johan, 2021).

financial sources after extreme weather events. Noteworthily, natural disasters are distinct sources of uncertainty compared with an economic recession, financial crises, political instability or terrorism (Doern, Williams and Vorley, 2019). Although all these events are exogenous and negatively impact the financial and economic stability of firms, natural disasters also engender physical destruction that may cause a reduction in the value of collateral, which limits a firm's ability to borrow from traditional lenders. In this regard, our paper provides novel empirical evidence that firms' ability to provide collateral to obtain funding from traditional sources is reduced after this kind of extreme event, thus firms increase their reliance on alternative finance.

Our results have important implications suggesting that alternative (non-traditional) sources of funding play a crucial role in both the survival and prosperity prospects of firms, as well as in the recovery of the economic regions affected by extreme unanticipated disruptions. Our findings support the view that alternative finance channels can meet firms' increased demand for credit after an extreme event, being a valuable remedy for the affected economies.

The remainder of this paper is structured as follows. In the next section, the key contributions to the literature on entrepreneurial finance and natural disasters are introduced and our research hypotheses are developed. The data are described in the third section, and the empirical model is presented in the fourth section. In the fifth section, the econometric results are reported and discussed; the sixth section concludes.

Literature review and research hypotheses

Natural catastrophes lead to an increase in loan requests to replace or repair damaged assets and a contemporary surge of deposit withdrawals, as affected individuals and firms must make up for the economic damage and increased current expenses (Brei, Mohan and Strobl, 2019). A growing literature analyses whether bank lending increases or decreases after a natural disaster, reaching mixed evidence. One view is that banks decrease credit supplied to affected areas and increase their holdings of government securities (Choudhary and Jain, 2017; Nguyen and Wilson, 2020; Schüwer, Lambert and Noth, 2019). The decline in bank lending results from a decline in the value of the collateral and the economic prospects of borrowers (both households and firms) in affected areas: new firms' loan applications are more likely to be rejected, and existing loans are likely to go unpaid, exposing bank balance sheets to unexpected losses and reducing the capacity of banks to transform risk. Banks may also suffer from a reduction in capital and deposits, which decreases the funds available for lending. By contrast, a few papers (Chavaz, 2016; Cortés and Strahan, 2017) suggest that banks increase lending in areas affected by natural disasters. Banks mitigate the impact of shocks by cutting lending most where their comparative advantage is least (i.e. where competing banks have similar access to information). For instance, banks increase lending in affected areas by decreasing financing in non-affected areas (Ivanov, Macchiavelli and Santos, 2020), or where banks do not have branches (Cortés and Strahan, 2017). Furthermore, few papers analyse the effect of extreme weather events on funding sources other than bank lending, such as insurance companies (Collier *et al.*, 2020; MacLaren *et al.*, 2017), grants (Gallagher, Hartley and Rohlin, 2020), trade credit (Casey and O'Toole, 2014), business loans (De Mel, McKenzie and Woodruff, 2013) and government transfers (Gallagher, Hartley and Rohlin, 2020). Overall, the extant evidence analyses the effect of natural disasters on traditional funding sources and, to the best of our knowledge, no papers are dealing with the role played by alternative finance channels. This is surprising given that alternative finance investments (e.g. crowdfunding, venture capital and angels) do not take into great account collateral in their lending decisions. Therefore, we argue that alternative finance funding may represent an additional source of lending at times of heightened uncertainty due to catastrophic events. Hence, our main research hypothesis is the following:

H1: After a natural disaster, firms increase the amount of funds collected through alternative finance sources.

This research hypothesis is also motivated by looking at the strand of literature that analyses the reaction of private funds to the global financial crisis (GFC). The few existing papers show that in the aftermath of the GFC, alternative finance channels are a viable and elective source of funding, especially for small and medium-sized enterprises (SMEs) (Ardic, Mylenko and Saltane, 2011; Casey and O'Toole, 2014) and start-ups (Zhang *et al.*, 2015). Although systemic financial crises and natural disasters are similar external shocks resulting in somehow similar effects (i.e. both are exogenous shocks for firms generating uncertainty and making it more difficult to raise funds both from traditional and alternative finance sources), a natural disaster has an additional and unique impact on firms: it generates physical destruction that causes a reduction in the value of collateral, which in turn limits firms' ability to borrow from traditional lenders but not from alternative finance sources. This difference makes a compelling case for the contribution of this study, highlighting the importance of testing our main research hypothesis H1.

To further explore the impact of extreme events on the availability of funding via alternative finance sources, we rely on the entrepreneurial finance literature (Harris and Raviv, 1991; Myers, 2003; Petersen and Rajan, 1994, 1995, among others), suggesting that firm size, physical capital intensity and age are essential factors affecting the ability of a firm to access finance. Firm size may enable access to disaster loans (among other mechanisms), which would help impacted firms to cope with the negative effects of such unexpected events (Doern, Williams and Vorley, 2019; Grube and Storr, 2018; Linnenluecke and McKnight, 2017; Monllor and Murphy, 2017; Williams and Shepherd, 2016). Large firms are more likely to have insurance in high-risk areas (Neumayer, Plumper and Barthel, 2014), which allows them to replace destroyed physical assets, often because business records that are required (for small firms) to access federal aid are lost in the floods and in the destruction of their buildings (Runyan, 2006). Heightened uncertainty during a crisis may also disproportionately affect SMEs. For instance, in the post-natural disaster period, smaller firms may be unable to secure loans with collateral and face higher interest rates (Collier *et al.*, 2020). Additionally, larger firms may be better placed to receive external funding as they are well known to investors (e.g. to private equity funds, as noted by Wilson, Amini and Wright, 2020), generate more geographically diversified cash flows and are less opaque since financial information is easily available and often reliable (Brown, Gustafson and Ivanov, 2020; Demirguc-Kunt, Peria and Tressel, 2020). However, there is no prior evidence in the literature on whether firm size matters for access to alternative finance in the aftermath of a catastrophic event. Thus, we posit:

H2: Larger firms are better placed to collect funds from alternative financial sources after a natural disaster.

Another essential determinant of a firm's access to finance is the availability of physical assets that could be used as collateral (Barro, 1976; Hart and Moore, 1994; Stiglitz and Weiss, 1981). Thus, capital-intensive industrial sectors (i.e. with larger investments in physical capital) may be more prone to get bank financing by pledging fixed assets. Nevertheless, once these firms are affected by a natural disaster, their ability to provide collateral on bank loans is reduced (Gan, 2007). In this line, empirical evidence shows that in the aftermath of a hazard event, banks seem to have expanded credit in categories associated with non-land collateral requirements (Koetter, Noth and Rehbein, 2020). Once again, these papers consider the impact of collateral on firm credit from mainstream funding sources, whereas there is no evidence on the role of collateral in a firm's access to alternative finance. By considering that physical asset usage differs across industries (e.g. IT firms rely less on physical assets than other industries), we test the following hypothesis:

H3: Firms in physical capital-intensive industries are more affected by natural disasters and thus increase their alternative finance collection.

Finally, various papers in the entrepreneurial finance literature suggest that firm age plays an essential role in a firm's access to credit. Firms with a long track record are likely to be less financially constrained than younger firms, which are still in the process of building a relationship with their lenders (Berlin and Mester, 1999; Boot, 2000; Rajan, 1992). Companies well known to investors may be better placed in obtaining finance in the aftermath of a natural disaster (Berg and Schrader, 2012). Moreover, much of the value of young innovative firms derives from intangible investment, thus increasing information asymmetries between founders and financiers and increasing the potential for credit rationing. Therefore, alternative finance can be more prominent for young firms as contracts can be structured to overcome these information asymmetries (Winton and Yerramilli, 2008). Furthermore, once young firms are affected by an adverse natural event, the exogenous increase in uncertainty prods these firms to seek funds from alternative finance sources; for example, leveraging on business similarity to mitigate problems associated with lack of knowledge of the investment (Shuwaikh and Hughes, 2020). The existing literature has not previously explored the access to finance of early-stage firms in the aftermath of extreme weather events. This leads us to develop and test a further hypothesis:

H4: Start-up firms increase fund collection from alternative finance after a natural disaster.

Lastly, yet importantly, the type of deal is another vital determinant of a firm's access to credit. Information asymmetries between owners and providers of finance affect the firm's choice of funding. To minimize costs associated with information asymmetry, pecking-order theory suggests that firms use retained earnings in preference to debt, and new equity is issued only as a last resort (Myers and Majluf, 1984). Generally, firms prefer sources of finance associated with the lowest level of information asymmetry. For example, Agrawal, Catalini and Goldfarb (2011) and Ahlers *et al.* (2015) argued that for equity crowdfunding, the lack of information is severe because gathering and assessing information from a distance (i.e. a web platform) is expensive. We fill in this crucial gap by investigating the following hypothesis:

H5: There is a positive relationship between the occurrence of a natural hazard and the increase in the amount of debt financing.

Data

We collect data on almost all funding raised by private firms using a wide range of products (e.g. equity crowdfunding and initial coin offering) and from various investors (e.g. family investment office and fund of funds). We gather information for approximately 39,000 US enterprises from the Crunchbase database from 2010 to 2019. Our dataset includes information on the total amount raised in each round by a firm and information on the investors (i.e. venture capital firms and angels) who provide the credit for the funding rounds.

Data on natural disasters are retrieved from the Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED) of the Université Catholique de Louvain. We focus on large-scale disasters in the United States between 2010 and 2019, as in the case of extreme weather events. We identify a natural event with economic losses exceeding USD 1 billion as extreme.[3] Economic and financial losses can either be insured, leading to losses for insurance companies, or uninsured, which means that losses are directly borne by financial institutions, enterprises and/or households. As an example, we analyse the following disasters: three disasters in the United States during the third quarter of 2017 – Hurricane Harvey (between 25/08/17 and 29/08/17), Hurricane Irma (between 10/09/2017 and 28/09/2017) and wildfires in California (between 08/10/17 and 20/10/2017). These events hit several US states, generating overall damages of USD 165 billion and affecting over 660,000 people. Figure 1 illustrates the total number of natural events by each US state between 2010 and 2019.

We construct two dummy variables to record the occurrence of a natural disaster event in a state. The first variable is at the state level ($Affected \times Post-Treatment_s$), taking the value 1 if a state has been hit by a natural disaster in a given month and the two subsequent months, and 0 otherwise. The second variable is at the firm level ($Affected \times Post-Treatment_i$), taking the value 1 if a firm is in a state hit by a natural disaster in a given month and the two subsequent months, and 0 otherwise.[4] Overall, we consider a 3-month time period to measure the post-disaster effect as done in previous studies (e.g. Garmaise and Moskowitz, 2009; Runyan, 2006). Table 1 reports the number of deals and amount of funds raised by type of

[3]Considering large events is part of our empirical strategy, as we are interested in situations where borrowers must change their normal course of action. Specifically, if for example losses are contained and do not affect a borrower's creditworthiness or borrowing prospects, we will be unable to test the hypotheses reported.

[4]We construct the dummy variable for natural disaster considering 3 months to account for the protracted effect of a natural event on the private funding market. Results are qualitatively the same if we consider just the month when a natural disaster occurs.

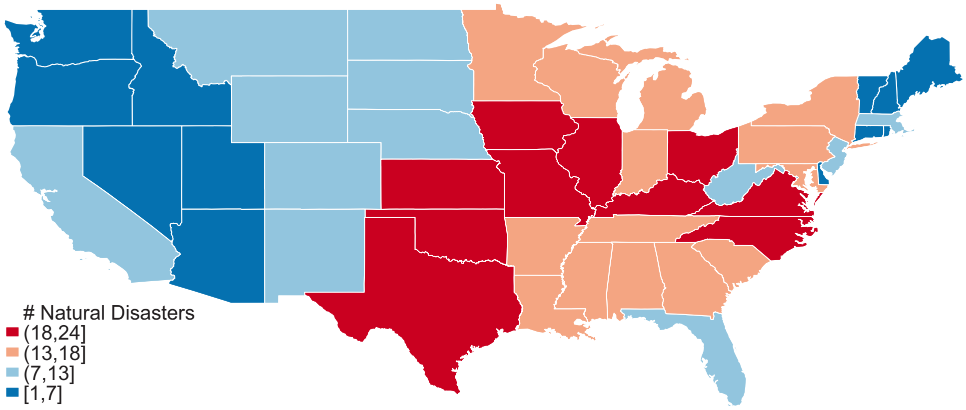

Figure 1. Total number of extreme natural events by US state (2010–2019)
This figure reports the number of natural disasters that generated economic losses exceeding USD 1 billion between 2010 and 2019. For each state, we compute the total number of events that occurred between 2010 and 2019. We then assign the states to each quartile of the distribution of the total events. The states highlighted in dark blue are in the first quartile of the distribution of the total number of natural disasters (between 1 and 7 events); those highlighted in light blue are in the second quartile of the distribution (between 8 and 13 events); those highlighted in light red are in the third quartile of the distribution (between 14 and 18 events); and those highlighted in dark red are in the fourth quartile of the distribution (between 19 and 24 events).
[Colour figure can be viewed at wileyonlinelibrary.com]

Table 1. Number of deals and amount of funds raised (USD million) by type of investment

	Before a natural disaster			After a natural disaster		
Funding type	No. rounds	$ millions	Average	No. rounds	$ millions	Average
Angel	1,569	1,505	0.96	545	504	0.93
Convertible note	1,354	3,060	2.26	513	2,770	5.40
Corporate round	145	18,889	130.27	58	16,765	289.06
Debt financing	3,784	91,863	24.28	1,420	40,502	28.52
Equity crowdfunding	425	575	1.35	198	224	1.13
Grant	1,947	8,998	4.62	583	2,548	4.37
Initial coin offering (ICO)	56	2,053	36.67	48	723	15.07
Non-equity assistance	49	138	2.81	10	14	1.39
Post-IPO debt	304	53,560	176.18	113	28,820	255.04
Post-IPO equity	1,057	50,948	48.20	389	30,056	77.26
Post-IPO secondary	4	2,701	675.30	2	3,100	1,550.00
Pre-seed	1,239	588	0.47	425	248	0.58
Private equity	689	83,163	120.70	264	33,808	128.06
Product crowdfunding	221	404	1.83	82	100	1.22
Secondary market	44	6,423	145.97	16	8,966	560.37
Seed	13,429	18,212	1.36	4,994	6,944	1.39
Series A and Series B	10,162	139,168	13.69	3,739	50,998	13.64
Other funding	14,260	247,833	17.38	5,298	101,246	19.11
	51,237	**739,000**	**14.42**	**18,697**	**328,336**	**17.56**

This table reports the number of deals, the amount (in USD million) and the average amount per deal (in USD million) by funding type for deals that occurred before a natural disaster and within 3 months after a disaster. The definition of each funding type appears in Appendix A.

investment. The largest number of deals is for later stage and more established companies (category labelled 'Other funding' in Table 1). The largest average size per funding round is in post-IPO secondary deals (USD 2.7 billion), when an investor purchases shares of stock in a company from other, existing shareholders, whereas the lowest average amount of funds raised is in the pre-institutional seed rounds (USD 0.47 million).

We also collect a wide range of macroeconomic data at the state level. State GDP growth rate (*GDP growth*) accounts for the overall economic development. Home price indexes (*House Prices*) capture decreases in the price of real assets that may impact the capacity of borrowers to raise funds. The amount of loans and leases provided by commercial banks (*Bank Loans & Leases*) accounts for the eventual competition generated by traditional banks on private funding markets. Data on macroeconomic variables are collected from the Federal Reserve of St. Louis (Federal Reserve Economic Data, FRED). Table 2 defines all the variables that we use in our study.

Table 3 reports the descriptive statistics for our sample. We consider approximately 70,000 funding rounds over the period 2010–2019. Approximately 21% of the total funding rounds are related to firms that raise funding just once (denoted as *Fund_new* in Table 2). Panel A describes firm-level data, whereas Panel B summarizes state-level data. Approximately 80% of the firms in our sample are small in size, whereas the remaining are mostly medium and some large. Half of the firms in our sample belong to IT-related industries, whereas approximately 36% of all firms are start-ups.

Methodology

To test whether funding provided by private investors is affected by a natural disaster, we run our analyses at two levels: first, we use a panel data sample at the state level, running a standard difference-in-differences (DiD) approach; second, we use pooled cross-sectional data (as in Hosono *et al.*, 2016; Schüwer, Lambert and Noth, 2019) to investigate the mediating role of the borrowers' characteristics accessing alternative finance after adverse natural events.

We first use the following DiD approach to estimate at the state level the aggregate effect of a natural disaster on the affected states. The specification is as follows:

$$\begin{aligned} \textit{Amount Raised}_{\mathrm{s,t}} = {} & \\ & \beta_1\ (\textit{Affected} \times \textit{Post} - \textit{Disaster})_{\mathrm{s}} \\ & + \beta_2 \textit{GDP growth}_{\mathrm{s,t}} + \beta_3 \textit{House Prices}_{\mathrm{s,t}} \\ & + \beta_4 \textit{Bank Loans}_{\mathrm{s,t}} + \alpha_{\mathrm{s}} + \alpha_{\mathrm{t}} + \varepsilon_{\mathrm{s,t}} \qquad (1) \end{aligned}$$

where the dependent variable is the log volume of private funding raised by firms in state s (e.g. California) in month t (e.g. January). The treatment group is identified by the variable *Affected* $\times$ *Post-Disaster$_i$*, i.e. a dummy variable capturing the occurrence of a natural disaster at the state level within 3 months after the natural disaster. The coefficient of main interest is β_1, as it enables us to test our first research hypothesis H1. Since natural disasters are exogenous shocks, our estimations do not suffer from endogeneity problems, and the coefficient β_1 estimates the causal average treatment effect (ATE) of natural disasters on the amount raised by alternative finance sources. The control group includes (a) all states that have not been affected by natural disasters at the time in which disasters affected other states and (b) all US states (both affected and non-affected) before the occurrence of natural disasters. At the state level, we control for various macroeconomic factors that may influence firms' funding ability, such as economic growth (measured by quarterly GDP growth – *GDP growth*), the value of properties (measured by the house price index – *House Prices*) and the size of the banking system (measured by the overall amount of commercial bank loans granted – *Bank Loans*). We take the natural logarithm of all the variables (except the dummy variable *Affected* $\times$ *Post-Disaster*) included in the estimations to limit problems associated with extreme values. We include month fixed effects (α_{t}) to capture time trends, and state fixed effects (α_{s}) to gauge unobservable state traits. Hence, we do not include in our model a dummy for a state treated by a natural disaster (*Affected*) and a time dummy for capturing the treatment (*Post-Disaster*) since these are absorbed by the state and month fixed effects. The coefficient of main interest is β_1, capturing the differential effect on private funding of the occurrence of natural disasters and expressing the average treatment effect between affected and non-affected states.

As a second step, we focus our analysis at the borrower level using pooled cross-sectional data to identify the idiosyncratic effect of a natural event on a firm source of funding. This approach allows us to investigate heterogeneous effects depending on firm characteristics. The specification is as follows:

$$\begin{aligned} \textit{Amount Raised}_{\mathrm{i,s,t}} = {} & \\ & \beta_1\ (\textit{Affected} \times \textit{Post} - \textit{Disaster})_{\mathrm{i}} \\ & + \beta_2 \textit{GDP growth}_{\mathrm{s,t}} + \beta_3 \textit{House Prices}_{\mathrm{s,t}} \\ & + \beta_4 \textit{Bank Loans}_{\mathrm{s,t}} + \alpha_{\mathrm{s}} + \alpha_{\mathrm{t}} + \alpha_{\mathrm{t*ind}} + \varepsilon_{\mathrm{s,t}} \quad (2) \end{aligned}$$

Table 2. List of variables

Variable	Acronym	Description
Total funds raised*	*Fund*	The amount (in USD million) of funds raised in any collection round.
Funds raised at the first round*	*Fund_new*	The amount (in USD million) of funds raised in the first collection round (i.e. collection round = 1).
Funds raised after the first round*	*Fund_old*	The amount (in USD million) of funds raised in rounds after the first (i.e. collection round > 1).
Natural disaster dummy+	*Affected × Post-Disaster*	A variable that takes the value 1 if a state (s) or a borrower (i) is affected by a natural event in a specific month and two subsequent months, and 0 otherwise.
GDP growth#	*GDP growth*	Percentage change by US state since the previous quarter of the total real gross domestic product.
Firm size*	*Size*	We consider three firm size dummy variables: small firms (taking the value 1 for companies with less than 100 employees, and 0 otherwise); medium-sized firms (taking the value 1 for companies with number of employees ranging between 100 and 1,000, and 0 otherwise); and large-sized firms (taking the value 1 for companies with more than 1,000 employees, and 0 otherwise).
Start-up firms*	*Start-up*	A variable that takes the value 1 if the difference between the date of funding and the firm's foundation date is less than 30 months, and 0 otherwise.
Non-IT firms*	*Non-IT*	A variable that takes the value 1 if firms do not belong to the IT sector. We reported two scores: the first (labelled 'whole') includes the entire dataset of firms; the second (labelled 'restricted') omits those firms slightly related to the IT or the non-IT sectors. The calculation procedure is reported in footnote 6.
Bank loans and leases#	*Bank loans*	Total loans and leases, net of unearned income for commercial banks.

This table reports the description, frequency and source of data included in the analyses. Data are obtained from the Crunchbase database (denoted *), the FRED database (#) and the EMDAT and CRED databases (+).

Table 3. Descriptive statistics

Panel A: Firm-level data	No. observations	Mean	Std dev.	Min.	Median	Max.
All sample						
Affected × *Post-Disaster*	69,934	0.267	0.443	0.000	0.000	1.000
Fund (in USD million)	69,934	14.669	1.872	6.488	14.626	23.273
Fund_new (in USD million)	14,686	13.999	1.982	6.488	13.864	22.690
Fund_old (in USD million)	55,248	14.848	1.800	6.908	14.845	23.273
Small firm	69,934	0.814	0.389	0.000	1.000	1.000
Medium firm	69,934	0.160	0.367	0.000	0.000	1.000
Large firm	69,934	0.025	0.157	0.000	0.000	1.000
Non-IT (restricted)	30,254	0.378	0.485	0.000	0.000	1.000
Non-IT (whole)	69,934	0.164	0.370	0.000	0.000	1.000
Start-up	69,934	0.365	0.482	0.000	0.000	1.000
Small firms						
Affected × *Post-Disaster*	56,935	0.268	0.443	0.000	0.000	1.000
Fund (in USD million)	56,935	14.295	1.691	6.488	14.310	21.947
Fund_new (in USD million)	13,318	13.772	1.808	6.488	13.816	21.947
Fund_old (in USD million)	43,617	14.454	1.620	6.908	14.509	21.128
Medium firms						
Affected × *Post-Disaster*	11,220	0.269	0.443	0.000	0.000	1.000
Fund (in USD million)	11,220	16.210	1.627	8.923	16.330	22.690
Fund_new (in USD million)	984	15.958	2.057	8.923	16.154	22.690
Fund_old (in USD million)	10,236	16.234	1.578	9.394	16.341	21.679
Large firms						
Affected × *Post-Disaster*	1,779	0.240	0.427	0.000	0.000	1.000
Fund (in USD million)	1,779	16.960	2.181	9.210	16.951	23.273
Fund_new (in USD million)	384	16.858	2.502	9.210	16.811	21.976
Fund_old (in USD million)	1,395	16.988	2.084	10.127	16.998	23.273
Non-IT = 1						
Affected × *Post-Disaster*	11,445	0.274	0.446	0.000	0.000	1.000
Fund (in USD million)	11,445	14.593	1.949	6.908	14.509	22.595
Fund_new (in USD million)	2,774	14.023	2.125	6.908	13.816	21.976
Fund_old (in $ million)	8,671	14.775	1.853	7.601	14.732	22.595
Start-up = 1						
Affected × *Post-Disaster*	25,553	0.275	0.446	0.000	0.000	1.000
Fund (in USD million)	25,553	13.918	1.679	6.908	13.911	22.690
Fund_new (in USD million)	7,227	13.574	1.748	6.908	13.528	22.690
Fund_old (in USD million)	18,326	14.054	1.631	6.908	14.039	20.918

Panel B: State-level data						
Affected × *Post-Disaster*	5,590	0.164	0.370	0.000	0.000	1.000
Fund (in USD million)	5,590	196.041	824.682	0.000	12.226	21,911.000
Fund_new (in USD million)	5,590	36.151	169.656	0.000	0.500	3,504.110
Fund_old (in USD million)	5,590	159.890	757.824	0.000	7.788	21,794.130
GDP growth (in percentage points)	5,590	0.150	0.006	0.000	0.000	8.532
House prices	5,590	367.732	122.620	182.560	336.200	950.750
Loan leases (in USD billion)	5,590	148.000	297.000	0.633	39.900	1,670.000

This table reports the summary statistics for the two samples we use in the paper (i.e. firm-level data in Panel A and state-level data in Panel B) for the period 2010–2019. All variables are described in Table 2.
Source of data: Crunchbase and FRED.

where the dependent variable is the volume of private funding raised by firm i in a funding round in month t. $Affected \times Post\text{-}Disaster_i$ is the dummy variable capturing the effect of natural disaster for firms in a state affected in comparison with non-affected firms, and the coefficient of main interest is β_1 as it enables us to test our first research hypothesis (H1). We run three different specifications to capture the effects of state, time and industry time-invariant unobservable factors. First, we include state fixed effects (α_s), then year fixed effects (α_t) and, in the last specification, we also saturate our model with (industry × year) fixed effects (α_{t*ind}). Since we used a pooled cross-sectional dataset,[5] our model is not a DiD model, but a simple difference model. However, natural disasters are exogenous shocks; therefore, our estimations do not suffer from endogeneity problems, and the coefficient β_1 estimates the causal ATE of natural disasters on the amount raised by alternative finance sources. As per Eq. (1), we take all variables (except the dummy $Affected \times Post{-}Treatment_i$) in natural logarithm.

As a third step, we introduce the role of borrower characteristics that may influence the ability to collect funds through alternative finance sources. Following our discussion in the literature review, we rely on the entrepreneurial finance literature, suggesting that firm size, physical capital intensity and age are essential factors that affect the ability of a firm to access finance. To this purpose, we extend Eq. (2) by introducing specific dummy variables to account for firm heterogeneity for each of these corporate features (firm size, physical capital intensity and age) as follows:

$$\begin{aligned}
&\textit{Amount Raised}_{i,s,t} = \\
&\quad \beta_1\ (\textit{Affected} \times \textit{Post} - \textit{Disaster})_i \\
&\quad + \beta_2 \textit{Firm Dummy}_i + \beta_3\ (\textit{Affected} \times \textit{Post} \\
&\quad - \textit{Disaster} \times \textit{Firm Dummy})_i \\
&\quad + \beta_4 \textit{GDP growth}_{s,t} + \beta_5 \textit{House Prices}_{s,t} \\
&\quad + \beta_6\ \textit{Bank Loans}_{s,t} + \alpha_s + \alpha_t + \alpha_{t*ind} + \varepsilon_{s,t} \quad (3)
\end{aligned}$$

where all variables are the same as in Eq. (2) and the variable *Firm Dummy* changes according to the corporate dimensions investigated. Specifically, we capture firm size using three dummy variables: *small size* (taking the value 1 for companies with less than 100 employees, and 0 otherwise); *medium size* (taking the value 1 for companies with number of employees ranging between 100 and 1,000, and 0 otherwise); and *large size* (taking the value 1 for companies with more than 1,000 employees, and 0 otherwise). To capture firm capital intensity, we generate the dummy variable *non-IT* taking the value 1 if firms do not belong to the IT sector.[6] Similarly, we capture the firm age using the dummy variable *start-up* that takes the value 1 if the difference between the date of funding and the firm's foundation date is less than 30 months; and 0 otherwise. Moreover, we capture the 'deal type' by generating two dummy variables: *debt financing* (taking the value 1 if the deal is a debt financing or grant, and 0 otherwise) and *seed* (taking the value 1 if the deal takes the form of angel, pre-seed or seed financing, and 0 otherwise). The coefficient of main interest is now β_3 for the triple interaction (*Affected* × *Post-Disaster* × *Firm Dummy*) i.e. the effect of a natural disaster for firms with a given characteristic in a state in comparison with non-affected firms. The estimated β_3 allows us to test all remaining research hypotheses (H2–H5).

Results

We first present the results of our DiD model in Eq. (1) using state-level data on the total amount of funds collected by all borrowers in all funding rounds. We run various models that are saturated by time and state fixed effects to capture invariant factors across states and time. In line with the studies pointing to an increase in the supply of funding

[5]Only in a few cases do we have that the same firms collect funds more than once. Hence, we are not able to construct panel data for firms collecting funds from alternative finance sources over time and observe the behaviour of firms affected by natural disasters before and after the natural disaster.

[6]The variable *non-IT sector* is a dummy variable that takes the value 1 for firms included in sectors not related to IT. This variable is obtained as follows. (1) According to the industry classification in the Crunchbase database, we defined the IT-related industries as follows: Apps, Artificial Intelligence, Electronics, Data and Analytics, Gaming, Hardware, Information Technology, Messaging and Telecommunications, Mobile, Navigation and Mapping, Platforms, Science and Engineering, and Software; all remaining industries are classified as not related to the IT sector. (2) Since firms are classified in more than one industry (e.g. a firm can be classified to be in the Artificial Intelligence, Data and Analytics, and Gaming sectors), we create a score for each firm in the sample by counting the number of occurrences in IT and non-IT sectors. (3) We create the IT and non-IT dummy using two approaches: first, we give the value 1 to the IT sector if the number of occurrences in IT sectors is greater than the number of occurrences in non-IT sectors; second, we run the same approach but remove all cases if the differences between occurrences in the two groups are 0 or 1. The second approach reduces the number of available observations from 69,934 to 30,242, but it enables us to omit all cases in which there is no clear evidence of the main industry for a firm.

Table 4. Alternative finance after a natural disaster: state-level evidence

Panel A: All funds collected	(1)	(2)	(3)	(4)
Affected × Post-Disaster	2.704***	2.416***	0.671***	0.467**
	(0.456)	(0.466)	(0.161)	(0.176)
GDP growth		0.042	−0.187***	−0.161
		(0.185)	(0.062)	(0.120)
House prices		1.101**	0.005	−0.288
		(0.470)	(0.451)	(0.306)
Bank loans & leases		6.625***	4.156***	0.148
		(1.644)	(0.597)	(1.154)
Observations	5,590	5,590	5,590	5,590
R-squared	0.022	0.172	0.581	0.599
State FE	No	No	Yes	Yes
Time (monthly) FE	No	No	No	Yes
Panel B: Total funds collected in the first round or in following rounds				
Affected × Post-Disaster	0.298	0.265	0.706***	0.416**
	(0.210)	(0.262)	(0.193)	(0.196)
GDP growth	−0.363***	−0.335**	−0.134*	−0.106
	(0.133)	(0.164)	(0.078)	(0.114)
House prices	0.537*	−0.142	−0.393	−0.516
	(0.272)	(0.259)	(0.514)	(0.409)
Bank loans & leases	9.497***	0.183	2.041**	0.217
	(1.019)	(1.573)	(0.784)	(1.705)
Observations	5,590	5,590	5,590	5,590
R-squared	0.472	0.503	0.587	0.603
State FE	Yes	Yes	Yes	Yes
Time (monthly) FE	No	Yes	No	Yes
Collection round	= 1	= 1	> 1	> 1

This table reports the results of the difference-in-differences model reported in Eq. (1). In Panel A, the dependent variable is the log value of recipient total funds collected by all borrowers in state s. In columns 1 and 2, we report estimates running a pooled OLS model; we include state fixed effects in column 3 and both state and time (monthly) fixed effects in column 4. In Panel B, columns 1 and 2, the dependent variable is the log value of recipient new funds (i.e. the first time a firm collects funds) collected by all borrowers in state s. In Panel B, columns 3 and 4, the dependent variable is the log value of recipient funds collected by all borrowers in state s that already collected funds in the past (i.e. funds collected after the first round). In both panels, the treatment group comprises the US states affected by a natural disaster over 3 months (*Affected × Post-Disaster*). The control group is composed of (a) other US states not affected by a natural disaster and (b) all US states (both affected and non-affected) in periods before the disaster. To remove confounding effects, we removed all observations in the 12 months before the natural disaster for all the affected states [we would like to thank our discussant at the conference on 'Entrepreneurial Finance in Honour of Mike Wright' for providing us with this suggestion]. We control for various macroeconomic factors (log-transformed) at the state level that may affect the amount of funds collected in the state: GDP growth, house prices and the overall amount of loans granted by commercial banks. All variables are defined in Table 2. The sample period is 2010–2019. Standard errors are clustered at the bank level and reported in parentheses.
*, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively.
Source of data: FRED and Crunchbase.

following natural disasters (Cortes and Strahan, 2017; Koetter, Noth and Rehbein, 2020), we show that the overall amount of funds raised through alternative finance sources by firms in states affected by a natural disaster is greater than that by firms in non-affected states (Table 4, Panel A). This result is consistent across specifications. Since natural disasters are exogenous shocks, our identification strategy is based on a DiD approach and our estimations do not suffer from endogeneity problems. Therefore, the coefficient β_1 (for the double interaction term *Affected × Post-Disaster*) shows the causal ATE of natural disasters on the amount raised by alternative finance sources. Focusing on the specification that includes both state and time fixed effects (Table 4, Panel A, column 4), we show that the overall amount of funds raised through alternative finance sources by firms in states affected by a natural disaster (in the following 3 months) is 47% greater than that by firms in non-affected states, providing clear support for our first research hypothesis (H1). Conversely, we do not find a similar effect for the overall amount of funds raised through the banking channel. As shown in Appendix Table B1, bank loans and leases collected by firms in affected and non-affected states do not display a statistically significant difference. Turning to macroeconomic factors, we report positive statistically significant estimates for the overall amount of loans granted by commercial banks, except for the specification with both time and state fixed effects. In general, the empirical evidence provided in this table confirms our main hypothesis that alternative financing sources such as private equity, crowdfunding and venture capital increase for affected states after a natural disaster due to the credit constraints imposed by the conventional funding sources.

In Table 4, Panel B we differentiate our analysis according to the funding round. Specifically, in the first two columns, we consider only those firms that borrowed money just once, controlling for state fixed effects (in column 1) and for both state and time fixed effects (in column 2). As explained above, information asymmetries are lower for known borrowers, in terms of facilitating firms' access to finance after an exogenous shock (Berg and Schrader, 2012). Conversely, in the last two columns, we consider those borrowers that have collected funds from alternative finance more than once. We report a positive statistically significant effect only for those firms that have previous experience in collecting funds through alternative channels. This increases the confidence of the investor (Capizzi, Croce and Tenca, 2020 and references cited therein) and thus facilitates the funding process in turbulent times, such as the aftermath of a natural disaster. Regarding the control variables, it appears that when the state of the economy is good, there is a reduction in the amount collected by firms participating for the first time in an alternative finance funding round. Finally, firms collect funds from alternative finance sources regardless of their previous experience in this type of funding, in periods when banks increase their supply of credit.

Next, we shift our focus to the firm level. In Table 5, Panel A we show that the coefficient of main interest (*Affected* $\times$ *Post-Disaster*) is positive and statistically significant in all regressions, showing that the amount of credit provided through non-traditional lenders is higher for firms in affected states within 3 months after the occurrence of a natural disaster. Our results strongly support our first research hypothesis (H1), suggesting that hazardous exogenous events (damaging severely the properties that can be used as collateral by firms that seek external funds by lowering their values) can negatively impact the credit lines from mainstream financial institutions such as banks, prodding firms to collect funds from alternative finance sources. This finding is also confirmed when we include firm fixed effects (Table 5, Panel A, column 5).[7] Concerning the macroeconomic factors, in most of the specifications, we observe a positive strong statistical relationship for bank loans in line with the view that banks react by increasing lending in the aftermath of a natural disaster (Chavaz, 2016; Cortés and Strahan, 2017). This suggests that it is easier for a firm to collect funds by alternative finance channels when the value of properties is higher and bank competition is high.

As before, we account for the different number of funding rounds a firm participated in. The results presented in Panel B of Table 5 demonstrate that the firms that have been affected by a natural disaster can raise funds from non-mainstream sources of credit, regardless of how many funding rounds they participated in at one time, albeit the statistical significance is lower in the case of firms with experience in raising alternative funds. Nevertheless, we note that lower economic conditions trigger an increase in borrowed funds only for firms with experience in raising alternative finance. Thus, it seems that the importance of alternative finance channels for firms increases when the economic growth is subdued; this is not surprising, since fund collection from standard channels (such as the banking one) is usually cyclical and thus declines when economic growth declines.

We now turn our attention to the borrower characteristics that may influence the ability to collect funds through alternative finance sources. To further explore the impact of extreme events on the availability of funding via alternative finance sources, we investigate how heterogeneity in firm size, physical capital intensity and age affects the ability of a firm to raise alternative funding.

First, we focus on the size of the enterprise. Specifically, we estimate Eq. (3), where the *firm*

[7]To include firm fixed effects, we exclude firms that have raised funds only once. Consequently, the total number of observations in column 5 is lower.

Table 5. Alternative finance after a natural disaster: firm-level evidence

Panel A: All funds collected	(1)	(2)	(3)	(4)	(5)
Affected × Post-Disaster	0.029*	0.033**	0.036**	0.034**	0.024*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.013)
GDP growth		−0.010	−0.017**	−0.015**	−0.022***
		(0.008)	(0.007)	(0.007)	(0.006)
House prices		0.307***	−0.010	0.085	1.366***
		(0.071)	(0.113)	(0.113)	(0.158)
Bank loans & leases		0.265***	0.224***	0.210***	0.318***
		(0.043)	(0.049)	(0.048)	(0.073)
Observations	69,934	69,934	69,934	69,934	46,793
Firms (#)	39,107	39,107	39,107	39,107	39,107
R-squared	0.048	0.052	0.106	0.118	0.794
Firm FE	No	No	No	No	Yes
State FE	Yes	Yes	Yes	Yes	No
Industry FE	No	No	Yes	No	No
Year FE	No	No	Yes	No	No
Year × Industry FE	No	No	No	Yes	Yes
Std error	Robust	Robust	Robust	Robust	Cluster

Panel B: Total funds collected in the first round or in following rounds				
Affected × Post-Disaster	0.065*	0.061*	0.029*	0.028
	(0.037)	(0.037)	(0.017)	(0.017)
GDP growth	−0.006	−0.004	−0.023***	−0.022***
	(0.018)	(0.018)	(0.008)	(0.008)
House prices	−0.248	−0.186	0.068	0.163
	(0.254)	(0.255)	(0.152)	(0.151)
Bank loans & leases	−0.022	−0.021	0.342***	0.335***
	(0.080)	(0.078)	(0.073)	(0.074)
Observations	14,670	14,670	55,245	55,245
Firms #	14,670	14,670	24,421	24,421
R-squared	0.113	0.143	0.105	0.118
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Year × Industry FE	No	Yes	No	Yes
Std error	Robust	Robust	Cluster firm	Cluster firm
Collection round	= 1	= 1	> 1	> 1

This table reports the results of the model in Eq. (2). In Panel A, the dependent variable is the log value of recipient total funds collected by firm i. In Panel B, the dependent variable is either the log value of the recipient total funds collected by firm i in the first round or in the following rounds. In all the specifications (except for column 5, Panel A), we report estimates obtained using the pooled cross-sectional sample. In column 5, we report the estimates of a panel data model: in this case, the number of observations is substantially lower since only a few firms collect funds more than once. The main variable of interest is (*Affected × Post-Disaster*), capturing the effect for all recipients in a US state affected by a natural disaster over 3 months after the occurrence of the disaster. This coefficient shows the (single) difference over firms in other US states that were not affected by the natural disaster and all firms in any US states (both affected and non-affected) in periods before the disaster occurred. We control for various macroeconomic factors (log-transformed) at the state level that may affect the amount of funds collected in a state: GDP growth, house prices and the overall amount of loans granted by commercial banks. The sample period is 2010–2019. All variables are defined in Table 2. Standard errors (either robust or clustered at the bank level) are reported in parentheses.

*, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively.

Source of data: FRED and Crunchbase.

dummy comprises a dummy variable (labelled size) capturing firm size (small, medium and large companies). Looking at the results in Table 6, we find that the size coefficient is positive and statistically significant for medium and especially large-sized firms. This is consistent with previous findings in the entrepreneurial finance literature, which documented that large-sized firms have access to all

Table 6. Alternative finance after a natural disaster: firm-level evidence of the role of the borrower's size

	(1) Small firm	(2) Medium firm	(3) Large firm
Affected × Post-Disaster	0.074**	0.025	0.031**
	(0.033)	(0.016)	(0.016)
Size	−1.952***	1.747***	2.311***
	(0.019)	(0.019)	(0.058)
Affected × Post-Disaster × Size	−0.049	0.039	0.280**
	(0.036)	(0.036)	(0.123)
GDP growth	−0.017**	−0.017**	−0.015**
	(0.007)	(0.007)	(0.007)
House prices	0.244**	0.176	0.155
	(0.104)	(0.107)	(0.111)
Bank loans & leases	0.240***	0.237***	0.210***
	(0.045)	(0.047)	(0.047)
Observations	69,934	69,934	69,934
Size (# of firms)	33,788	4,401	928
R-squared	0.279	0.233	0.157
State FE	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes
Std error	Robust	Robust	Robust

This table reports the results of the model in Eq. (3), where the dependent variable is the log value of recipient total funds collected by firm i. We report estimates obtained using the full pooled cross-sectional sample, including state and industry year fixed effects. In each regression, the variable size represents small-sized firms (column 1), medium-sized firms (column 2) or large-sized firms (column 3), as defined in Table 2. The variables of main interest are (a) the interaction *Affected × Post-Disaster*, capturing the effect for all recipients in a US state affected by a natural disaster over 3 months following the disaster and (b) the interaction *Affected × Post-Disaster × Size*, capturing the effect for all recipients with a given dimension (measured by the number of employees) in a US state affected by a natural disaster over 3 months after the disaster. We control for various macroeconomic factors (log-transformed) at the state level that may affect the amount of funds collected in the state: GDP growth, house prices and the overall amount of loans granted by commercial banks. The sample period is 2010–2019. All variables are defined in Table 2. Standard errors are robust and reported in parentheses. *, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively.
Source of data: FRED and Crunchbase.

sorts of financing channels because of their size and the amount of collateral that they pledge to creditors. The coefficient of main interest is the triple interaction (*Affected × Post-Disaster × Size*) showing the effect produced by a natural disaster on firms located in an affected state, distinguishing among firms with small size (column 1), medium size (column 2) and large size (column 3), in comparison with non-affected firms of a similar size. The sign, magnitude and statistical significance of these coefficients enable us to test our second research hypothesis (H2). Although all affected firms increase fund collection by alternative finance sources in the aftermath of a natural disaster (i.e. coefficient estimates for *Affected × Post-Disaster* are positive and statistically significant), the coefficient for the triple interaction term (*Affected × Post-Disaster × Size*) is positive and statistically significant at the 5% confidence level only for large-sized firms. This suggests that large companies have an advantage in using alternative finance channels in comparison with non-affected firms. Besides past papers on entrepreneurial finance documenting that large-sized firms can access credit more easily than can smaller firms, we now show that large companies have an advantage using alternative finance channels, supporting our second research hypothesis (H2). Moreover, since the role played by collateral in lending decisions is minor in alternative investments, we argue that the advantage that large-sized firms possess in accessing alternative finance channels after a natural disaster is because these firms are well known in the market and there is a provision of reliable and easily available information on them, rather than the availability of physical assets to be pledged as collateral.

Furthermore, we investigate whether firms having physical assets to be pledged as collateral in bank loans have a lower incentive to collect funds using alternative finance sources both in general and after a natural disaster (Table 7). Since the

Table 7. Alternative finance after a natural disaster: firm-level evidence of the role of a borrower's industry

	(1)	(2)	(3)	(4)
Affected × Post-Disaster	−0.000	−0.000	0.009	0.009
	(0.029)	(0.030)	(0.021)	(0.021)
Non-IT	0.041	0.037	0.097***	0.096***
	(0.051)	(0.051)	(0.021)	(0.021)
Affected × Post-Disaster × Non-IT	0.105**	0.096**	0.062**	0.056*
	(0.048)	(0.049)	(0.030)	(0.031)
GDP growth	−0.030***	−0.029**	−0.017**	−0.015**
	(0.011)	(0.011)	(0.007)	(0.007)
House prices	0.306*	0.403**	−0.014	0.082
	(0.177)	(0.178)	(0.113)	(0.113)
Bank loans & leases	0.310***	0.327***	0.227***	0.213***
	(0.079)	(0.079)	(0.049)	(0.048)
Observations	30,242	30,242	69,934	69,934
Firm (#)	16,743	16,743	39,107	39,107
R-squared	0.098	0.113	0.106	0.118
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Year × Industry FE	No	Yes	No	Yes
Std error	Robust	Robust	Robust	Robust

This table reports the results of the model in Eq. (3), where the dependent variable is the log value of recipient total funds collected by firm i. We report estimates obtained using the full pooled cross-sectional sample. The variable *non-IT sector* is a dummy variable that takes the value 1 for firms included in sectors not related to IT. This variable is obtained as follows. (1) According to the industry classification in the Crunchbase database, we defined the IT-related industries as follows: Apps, Artificial Intelligence, Electronics, Data and Analytics, Gaming, Hardware, Information Technology, Messaging and Telecommunications, Mobile Phones, Navigation and Mapping, Platforms, Science and Engineering, and Software; all remaining industries are classified as not related to the IT sector. (2) Since firms are classified in more than one industry (e.g. a firm can be classified to be in the Artificial Intelligence, Data and Analytics, and Gaming sectors), we create a score for each firm in the sample by counting the number of occurrences in the IT and non-IT sectors. (3) We create a non-IT dummy using two approaches: first, we give the value 1 to the IT sector if the number of occurrences in IT sectors is greater than the number of occurrences in non-IT sectors; second, we run the same approach, but we remove all cases if the absolute value of the differences between occurrences in the two groups is 0 or 1. The second approach reduces the number of available observations from 69,934 to 30,242, but it enables us to omit all cases in which there is no clear evidence of the main industry for a firm. Hence, the variable non-IT sector is computed using the restricted sample in columns 1 and 2, and the full sample in columns 3 and 4. The variables of main interest are (a) the interaction *Affected × Post-Disaster*, capturing the effect for all recipients in a US state affected by a natural disaster over 3 months following the disaster and (b) the interaction *Affected × Post-Disaster × Non-IT*, estimating the effect for all recipient industries different from IT in a US state affected by a natural disaster over 3 months following the disaster. We control for various macroeconomic factors (log-transformed) at the state level that may affect the amount of funds collected in the state: GDP growth, house prices and the overall amount of loans granted by commercial banks. The sample period is 2010–2019. All variables are defined in Table 2. Standard errors are robust and reported in parentheses.
*, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively.
Source of data: FRED and Crunchbase.

classification of industries relying more on physical assets may be subjective, we create a dummy variable for all firms in IT sectors[8] (where the availability of physical assets is in most cases less relevant for obtaining credit) and a dummy variable for firms in non-IT sectors. In Table 7, the coefficient of main interest is the triple interaction (*Affected × Post-Disaster × Non-IT*) showing the effect produced by a natural disaster on firms non-related to the IT industry and located in an affected state in comparison with non-affected firms: the sign, magnitude and statistical significance of these coefficients enable us to test our third research hypothesis (H3). Generally, we find that the coefficient estimate for *non-IT* is not statistically significant (at the 10% level or less) for firms whose

[8]The variable *non-IT sector* is a dummy variable that takes the value 1 for firms included in sectors that are not related to IT (as described in footnote 6). The variables of main interest are the interaction (*Affected × Post-Disaster*), capturing the effect for all recipients in an affected US state.

Table 8. Alternative finance after a natural disaster: firm-level evidence of the role of a borrower's age

	(1)	(2)	(3)
Affected × Post-Disaster	0.034*	0.022	0.020
	(0.020)	(0.020)	(0.020)
Start-up	−1.240***	−1.140***	−1.139***
	(0.016)	(0.016)	(0.016)
Affected × Post-Disaster × Start-up	0.046	0.055*	0.059**
	(0.030)	(0.029)	(0.029)
GDP growth	−0.003	−0.011	−0.009
	(0.007)	(0.007)	(0.007)
House prices	0.183***	−0.092	0.009
	(0.069)	(0.108)	(0.108)
Bank loans & leases	0.255***	0.179***	0.169***
	(0.043)	(0.048)	(0.047)
Observations	69,934	69,934	69,934
Firm #	39,107	39,107	39,107
R-squared	0.150	0.185	0.195
State FE	Yes	Yes	Yes
Year FE	No	Yes	No
Year × Industry FE	No	No	Yes
Std error	Robust	Robust	Robust

This table reports the results of the model in Eq. (3), where the dependent variable is the log value of recipient total funds collected by firm i. We report estimates obtained using the full pooled cross-sectional sample. The variable *Start-up* is a dummy taking the value 1 for all recipients with firm's age inferior to 30 months. The main variables of interest are (a) the interaction *Affected × Post-Disaster*, capturing the effect for all recipients in a US state affected by a natural disaster over 3 months following the disaster and (b) the triple interaction *Affected × Post-Disaster × Start-up* capturing the effect for all start-up recipients in a US state affected by a natural disaster over 3 months after the disaster. We control for various macroeconomic factors (log-transformed) at the state level that may affect the amount of funds collected in the state: GDP growth, house prices and the overall amount of loans granted by commercial banks. The sample period is 2010–2019. All variables are defined in Table 2. Standard errors are robust and reported in parentheses.
*, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively.
Source of data: FRED and Crunchbase.

primary business is in non-IT sectors (Table 7, columns 1 and 2). By contrast, firms that combine IT and non-IT businesses collect larger sums from non-alternative finance sources (Table 7, columns 3 and 4). This suggests that businesses primarily operating in non-IT sectors – usually having a greater physical asset intensity, and thus a greater capability to provide collateral to banks than firms in the IT industry – raise less funding from alternative finance sources. Nonetheless, the coefficient estimate for the interaction term (*Affected × Post-Disaster × Non-IT*) is positive and statistically significant at the 5% level. Additionally, the greater magnitude of the coefficients for the interaction term in the regressions with firms whose primary business is non-IT (Table 7, columns 1 and 2) confirms our third research hypothesis (H3): once affected by natural disasters that damage their properties, firms having a greater physical asset intensity (the ones more exposed to disruption) are less able to provide collateral in traditional finance (e.g. bank loans) and thus increase their funding collection through alternative finance collection.

As a next step, we focus our attention on firm start-ups by considering whether firm age plays an important role in gaining access to non-mainstream credit lines. Specifically, we define a start-up dummy variable (i.e. *start-up* takes the value 1 if the difference between the date of funding and the firm's foundation date is less than 30 months, and 0 otherwise). In Table 8, the coefficient of main interest is the triple interaction (*Affected × Post-Disaster × Start-up*) showing the effect produced by a natural disaster on firms founded less than 30 months ago and located in an affected state in comparison with non-affected firms: the sign, magnitude and statistical significance of these coefficients enable us to test our fourth research hypothesis (H4). Overall, we find that the coefficient estimate for *start-up* is negative and statistically significant (at the 1% level), suggesting that companies funded less than 30 months

Table 9. Alternative finance after a natural disaster: firm-level evidence of the deal type

	(1) Debt financing	(2) Debt financing	(3) Seed	(4) Seed
Affected × Post-Disaster	0.025	0.022	0.235***	0.234***
	(0.016)	(0.016)	(0.018)	(0.018)
Deal type	−0.559***	−0.568***	−1.368***	−1.358***
	(0.028)	(0.028)	(0.014)	(0.014)
Affected × Post-Disaster × Deal Type	0.107**	0.109**	−0.662***	−0.659***
	(0.053)	(0.053)	(0.027)	(0.027)
GDP growth	−0.018**	−0.016**	−0.012*	−0.011
	(0.007)	(0.007)	(0.007)	(0.007)
House prices	−0.015	0.082	0.115	0.187*
	(0.112)	(0.112)	(0.104)	(0.105)
Bank loans & leases	0.212***	0.199***	0.202***	0.185***
	(0.048)	(0.048)	(0.046)	(0.046)
Observations	69,934	69,934	69,934	69,934
Firm (#)	39,107	39,107	39,107	39,107
R-squared	0.113	0.126	0.234	0.243
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Year × Industry FE	No	Yes	No	Yes
Std error	Robust	Robust	Robust	Robust

This table reports the results of the model in Eq. (3), where the dependent variable is the log value of recipient total funds collected by firm i. We report estimates obtained using the full pooled cross-sectional OLS model sample. In each regression, the dummy variable ‘deal type’ either represents funds collected as debt funds in the form of debt financing or grant (columns 1 and 2) or seed in the form of angel, pre-seed or seed financing (columns 3 and 4). The variables of main interest are (a) the interaction *Affected* × *Post-Disaster*, capturing the effect for all recipients in a US state affected by a natural disaster over 3 months after the disaster and (b) the triple interaction *Affected* × *Post-Disaster* × *Deal Type*, capturing the effect for all recipients of a given deal type in a US state affected by a natural disaster over 3 months after the disaster. We control for various macroeconomic factors (log-transformed) at the state level that may affect the amount of funds collected in the state: GDP growth, house prices and the overall amount of loans granted by commercial banks. The sample period is 2010–2019. All variables are defined in Table 2. Standard errors are robust and reported in parentheses.

*, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively.

Source of data: FRED and Crunchbase.

ago, on average, collect a lower amount of funds than more established firms. To estimate the differential effect for start-up firms affected by natural disasters relative to non-affected firms, we focus on the coefficient estimates for the triple interaction term (*Affected* × *Post-Disaster* × *Start-up*); this is positive and statistically significant at the 5% level or less in the most complete specification of Eq. (2) (columns 2 and 3 in Table 8), supporting our fourth hypothesis (H4). Once affected by natural disasters, start-up firms increase fund collection from alternative finance channels in comparison with non-affected firms.

Finally, yet importantly, we consider the type of deal of the fund collection from alternative credit channels (Table 9). Data availability enables us to differentiate deals into two main categories, debt financing (columns 1 and 2) and early-stage financing (columns 3 and 4). The coefficient of main interest is the triple interaction (*Affected* × *Post-Disaster* × *Deal Type*) showing the effect produced by a natural disaster on firms located in an affected state for a given deal type (either debt financing or seed) in comparison with non-affected firms: the sign, magnitude and statistical significance of these coefficients enable us to test our fifth research hypothesis (H5). As shown in Table 9, the coefficient estimate for *Deal Type* is negative and statistically significant (at the 1% level) for both debt financing deals and seed deals, suggesting that both these types of deals generally collect lower amounts of funds than other deal types. We capture the differential effect for each of these two deal types for firms affected by natural disasters relative to non-affected firms through the coefficient of the triple interaction term (*Affected* × *Post-Disaster* × *Deal Type*). The estimates are positive and statistically significant at the 5% level for debt financing (meaning that in the aftermath of an extreme event, firms collect more external financial resources in the form of debt financing in comparison with non-affected firms, as shown in Table 9, columns 1 and 2), whereas coefficient estimates for seed deals are negative and statistically significant at the 1% level (meaning that in the aftermath of an extreme event, firms collect less external financial resources in the form of seeds relative to non-affected firms, as shown in Table 9, columns 1 and 2). These results are not surprising since natural disasters negatively impact fund collection through bank loans (disrupting physical assets that firms may provide as collateral) and prod affected firms to seek alternative debt financing sources. Conversely, early-stage financing involves raising lower amounts in general and even lower amounts in the aftermath of a natural disaster. This is because the informational asymmetries are more severe for the financing of early-stage ventures and firms may find it difficult or costly to raise money as investors may be reluctant to acquire ownership in an early-stage company (i.e. seed type). Generally, our results support our fifth research hypothesis (H5).

Conclusion

In this paper, we investigate the flow of funding to firms after a natural disaster. We focus on non-bank lending and analyse firm characteristics that explain differences in the amount of funds raised after a natural disaster. We argue that natural disasters have a calamitous impact on firms' available sources of credit because they damage firms' economic prospects and the value of tangible assets that could be used as collateral. In turn, lower collateral may clog funding from mainstream lenders and exacerbate firm financial distress. Hence, we investigate whether alternative finance (such as private equity, crowdfunding and venture capital) is a viable and available source of funds for a large sample of US firms affected by natural disasters during the last decade.

We provide strong empirical evidence (using data both at the firm and state level) that within 3 months after the occurrence of a natural disaster, the amount of funds raised by non-traditional lenders increases for firms in state(s) affected by the event. We find that financing through alternative sources increases for large-sized firms, non-IT firms and start-up firms. The amount raised through debt financing is also larger, whereas early-stage financing is negatively affected when experiencing a hazardous event.

Our results have important implications for policymakers. When an exogenous catastrophic shock hits the economy, physical assets are damaged, firm capability to pledge collateral (required in traditional lending) is weakened, and thus firms may find it difficult to raise financial resources for the reconstruction. Our paper shows that alternative sources of funding become particularly prominent for firms after extreme natural events, and that firm heterogeneity is essential to detect which firms are more negatively affected by these hazardous events. Smaller, less well-known and more opaque firms are at a relative disadvantage and could see a drop in the amount of funds raised through alternative sources.

Our findings may inform the design of financial policies in reaction to economic uncertainty. The heterogeneity of the outcomes shown in our paper plays an essential role from a policy perspective when deciding whether to support firms in areas hit by a natural disaster. Targeted interventions may aim to support short-term financial needs through, for example, grants, subsidies or loan guarantees. Furthermore, enlisting the help of the private sector through, for instance, collaborative partnerships (Xing, Liu and Cooper, 2018) may entail a more transparent allocation of resources, ensuring that financing reaches the most affected enterprises efficiently.

Our study presents some limitations that are useful starting points for future research. First, we do not investigate the financial management dynamics of firms affected by natural disasters.[9] In this regard, one may assume that large-sized firms take alternative sources of financing to meet their short-term cash flow needs, and that this funding could be a small proportion of their total debt/long-term/short-term debt. However, the availability, usage and impact of alternative sources of financing may be relatively more significant for small and medium-sized enterprises because of their capital needs in hard times. Future research may build a new dataset by matching alternative finance deals and firm data (as asset,

[9]We would like to thank one of the referees for this constructive comment and for providing suggestions for future research.

liability, cost and income items) that will allow researchers to develop an identification strategy free of endogeneity concerns. Similarly, new data could be collected to assess the overall negative impact of extreme weather events, for example, in terms of business failure, overall financing of affected firms and/or resource losses. Moreover, unattended demand for financing could be captured by gathering information on rejected requests for funding. Finally, future work could incorporate in the analysis essential features such as the presence of nonlocal investors and their role in mitigating the effects of localized disasters, the role of different types of lenders, deals and learnings from past disasters, and differentiate the impact by type of natural disaster (climatological, hydrological, meteorological and geophysical).

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Konstantinos N. Baltas is an Assistant Professor of Banking and Finance at Essex Business School, University of Essex. His research focus is in the fields of banking, financial economics, macro prudential policy and financial intermediation. His current and on-going research lies in the area of financial stability, financial management and efficiency, with specific interest in regulation, competition, monetary policy, household finance, corporate governance and risk. He has published in leading international journals.

Franco Fiordelisi is Professor of Banking and Finance at Essex Business School, University of Essex. He is also President of the Financial Intermediation Network of European Studies (FINEST). His research has been published in the *Journal of Financial and Quantitative Analysis*, *Review of Finance*, *Journal of Financial Intermediation* and *Journal of Corporate Finance*. Franco is currently Associate Editor of the *Journal of Financial Stability*, *European Journal of Finance,* and *Economic Modelling*.

Davide S. Mare is a Research Economist at the World Bank's Development Research Group, leading the update of the World Bank – Bank Regulation and Supervision survey. His main research interests lie in banking, focusing on bankruptcy prediction, credit risk, competition and efficiency. Davide is an expert in the assessment of the individual bank risk of default and in applied financial valuation. His work has appeared in leading international journals and reports.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Types of funding in alternative finance
Appendix B: Estimations with bank loans as the dependent variable
Table B1: Bank loans after a natural disaster – state-level evidence