Article:

Huang, C., Zhang, A., Zhang, M. et al. (1 more author) (2024) Venture capital and vulnerability: navigating natural disasters and investment resilience. European Financial Management. ISSN 1354-7798

https://doi.org/10.1111/eufm.12528

European Financial Management

WILEY

EUROPEAN FINANCIAL MANAGEMENT

ORIGINAL ARTICLE OPEN ACCESS

Venture Capital and Vulnerability: Navigating Natural Disasters and Investment Resilience

Chen Huang[1] | Aoran Zhang[2] | Mengyu Zhang[3] | Yunfei Zhao[4]

[1]School of Business and Management, Queen Mary University of London, London, UK | [2]Ted Rogers School of Management, Toronto Metropolitan University, Toronto, Ontario, Canada | [3]Sheffield University Management School, University of Sheffield, Sheffield, UK | [4]College of Business and Public Management, Wenzhou-Kean University, Wenzhou, Zhejiang Province, China

Correspondence: Chen Huang (chen.huang@qmul.ac.uk)

Received: 30 June 2024 | **Revised:** 4 October 2024 | **Accepted:** 17 October 2024

Funding: The authors received no specific funding for this work.

Keywords: climate risk | entrepreneurial companies | Natural disasters | venture capital

ABSTRACT

This study examines the impact of natural disasters on venture capital (VC) investment decisions. Using 47 catastrophic natural disasters occurred in the United States from 1990 to 2019, our empirical analysis reveals a significant reduction in VC investments in disaster zones. Additionally, natural disasters negatively influence VC exit strategies, reducing the likelihood and extending the time to successful exits via IPOs. However, we find that green VCs are more likely to invest in disaster-affected areas, indicating potential resilience through green technological innovation. Our findings emphasize sustainability and disaster mitigation, and offer valuable insights for policymakers and investors amidst rising climate uncertainties.

JEL Classification: G1, G20, G24, M13, Q54

1 | Introduction

As financial intermediaries, venture capitalists (VCs) provide both financial and managerial support to entrepreneurial companies, fostering economic development over the past few decades (Andrieu and Groh 2018; Fried and Hisrich 1988). In 2021, global VC reached $671 billion, nearly double the total from 2020 (Moore 2023). With its well-developed financial system and capital markets, the United States (US) has played a leading role in the global VC ecosystem, accounting for over half ($345.4 billion) of global VC investments. Moreover, approximately 60% of US investment deals were concentrated in five states: California, Massachusetts, New York, Texas and Florida (National Venture Capital Association 2023). Notably, four of these five states (California, New York, Texas and Florida) are among the most disaster-prone, enduring a variety of devastating and frequent climate events, such as floods, tornadoes, ice storms, droughts and wildfires, according to the US News and World Report[1].

The implications of climate risk associated with natural disasters have been comprehended by capital market participants. A survey conducted by FM Global, one of the largest property insurers in the world, reveals that 76% of CEOs and CFOs believe that natural disasters and climate change pose significant financial and operational risks to their companies[2]. In addition, Institutional investors have also acknowledged the growing climate risks. Krueger, Sautner, and Starks (2020) surveyed institutional investors globally, finding that most believe climate-related risks have already influenced their investment decisions, with many taking concrete steps to manage such risks. Indeed, Alok, Kumar, and Wermers (2020)

All authors contributed euqally to this paper.
Consistent with EFM guidlines, authors are listed in alphabetical order.

provide empirical evidence that natural disasters increase mutual fund managers' risk aversion, leading them to reduce portfolio allocations to equities in disaster zones. However, none of these studies explore how the occurrence of natural disasters affects VC investment decisions. This paper seeks to bridge this gap by investigating the unexplored determinants of VC investments, specifically examining the extent to which natural disasters affect VCs′ investment decisions in their portfolio companies[3].

Natural disasters in this context refer primarily to weather-related events such as extreme temperatures, floods, droughts, blizzards, hurricanes, typhoons and wildfires, as well as geological events like earthquakes and volcanic eruptions (Klomp and Valckx 2014). Beyond environmental and infrastructure damage, natural disasters frequently cause significant financial and human losses (Crowards 2000; Rasmussen 2004). For example, the Northridge earthquake in California in 1994 ($78 billion), Hurricane Katrina in 2005 ($165 billion) and Hurricane Harvey in 2017 ($130 billion) rank among the costliest disasters in financial terms. Despite disaster-resilience policies enacted by agencies like the Environmental Protection Agency (EPA), the financial costs associated with natural disasters continue to escalate[4],[5].

Chaney, Sraer, and Thesmar (2012) argue that natural disasters negatively impact corporate investment and financing decisions by compromising pledgeable assets used as collateral. Natural disasters can damage tangible assets, such as property, machinery and plants, which are essential for a company's operations. Moreover, the time needed to restore production processes and reconstruction during the post-disaster period disrupts cash flow and increases the need for external financing. These challenges are particularly problematic for VCs. Previous studies have shown that VC investments decline during economic and financial crises due to unfavorable macroeconomic conditions (Jeng and Wells 2000; Ning, Wang, and Yu 2015). Conti et al. (2019) demonstrate that during the 2008 financial crisis, VCs adjusted their investment strategies by focusing on their core sectors. Additionally, Félix, Pires, and Gulamhussen (2013) emphasize the importance of IPO and M&A markets for VC financing, as these are associated with the existence of sophisticated financial markets that provide more investment opportunities and incentives for VC activity (Black and Gilson 1998; Nahata, Hazarika, and Tandon 2014). Further, VCs typically receive funding from limited partners (LPs) to invest in high-risk ventures such as startups (Ewens and Rhodes-Kropf 2015). Thus, ensuring the profitability of these investments and maintaining relationships with LPs is crucial for VCs (Tian, Udell, and Yu 2016). If natural disasters disrupt local economic conditions and hinder the operations of startups, thereby reducing the likelihood of successful IPOs or M&As, VCs may become more hesitant to invest.

Moreover, studies by Kaplan and Strömberg (2004) and Bertoni and Groh (2014) suggest that information asymmetry between startups and VCs is a critical factor in determining the success of VC investments. VCs need to gather comprehensive information from startups to assess their growth potential before making investment decisions. However, natural disasters can exacerbate information asymmetry in the market (Alok, Kumar, and Wermers 2020; Akter, Cumming, and Ji 2023). For instance, Akter, Cumming, and Ji (2023) report that natural disasters are linked to increased market manipulation, resulting in greater information disparity. Thus, the resulting disorder in local markets during post-disaster periods can hinder VCs′ ability to monitor startup performance, thereby delaying the investment process.

Additionally, natural disasters can impact innovation outcomes. Chen et al. (2021) reveal that natural disasters negatively affect technological innovations. Zhao, Zheng, and Fu (2022) document the adverse effects of natural disasters on energy technology innovation. Corporate innovation is a critical performance signal for startups in the VC market. Research by Hellmann and Puri (2000) and Hsu and Ziedonis (2011) shows that more innovative companies are more likely to secure VC funding and receive higher valuations. If natural disasters hamper corporate innovation, VCs may become more conservative in their investment decisions. In this context, the concentration of natural disasters could reduce the potential benefits that VCs expect from their portfolio companies. Based on this discussion, we hypothesize that *natural disasters prompt VCs to adopt more conservative investment strategies due to operational disruptions and heightened information asymmetry*.

To empirically assess whether natural disasters affect VC investment decisions, we collect data on VC transactions and natural disasters in the United States from 1990 to 2019, constructing a sample of 323,885 firm-quarter observations. To quantify the damage caused by climate-related disasters, we use property damage data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). Given the variability in the extent of damage across different disasters and the increasing frequency of large-scale events in recent years, we define 47 major disasters to minimize potential identification bias in our empirical results (Barrot and Sauvagnat 2016). Specifically, we include disasters that resulted in more than $1 billion in losses within a 31-day period between 1990 and 2019.

Using a variety of econometric techniques and robustness checks, incorporating alternative proxies for VC investments and climate disasters, our empirical analysis reveals a significant negative impact of natural disasters on VC investment decisions within the four quarters following the disaster. Specifically, VCs make fewer investments in portfolio companies located in disaster-affected areas compared to those in unaffected areas. Economically, a one-standard-deviation increase in the damage ratio corresponds to a 14.74% drop in VC investments in startups in disaster zones. We consider this economic effect substantial, as it represents an approximate $200,000 reduction in the average investment. Additionally, while the negative impact on VC investments in disaster-affected portfolio companies diminishes over time, it can persist for up to four quarters after the event.

Next, we explore how natural disasters affect VC exit strategies. We identify two aspects of the exit mechanisms: the choices and timing of VC exits. Our findings show that natural disasters reduce the likelihood of successful VC exits, whether through IPOs or acquisitions, for portfolio companies in disaster-affected areas within four quarters after the disaster. For example, a one-standard-deviation increase in the damage ratio is associated with a 54 basis point reduction in the probability of a successful exit. Even in cases where VCs successfully exit from their investments, the likelihood of achieving an IPO—the most desirable exit option—is significantly lower compared to exits via trade sales. Furthermore, survival analysis reveals that VCs take significantly longer to cash out through IPOs from startups located in disaster-affected areas.

We also examine the mechanisms through which natural disasters discourage VCs from funding young ventures. Our results show that the negative effect of natural disasters on VC investments is more pronounced in startups with high levels of tangible assets, suggesting that firms with substantial tangible assets are more exposed to climate-related risks. Additionally, industry-level analysis indicates that this negative effect is particularly significant in industries with a large proportion of fixed assets, reinforcing the relationship between asset tangibility and vulnerability to disasters.

In our baseline analysis, we account for the overall damage caused by all types of natural disasters. However, different disaster types may impact VC investment decisions in varying ways. To investigate this, we examine specific disaster types, including hurricanes/typhoons, floods, winter storms, wildfires and earthquakes. The results confirm that all these disaster types negatively affect VC investments, consistent with our baseline findings. Furthermore, our results indicate that natural disasters increase the financing costs for startups seeking VC funding. Previous studies, such as El Ghoul et al. (2023), document that climate-related disasters raise the cost of debt financing, particularly for firms with high leverage. Disasters significantly damage corporate assets, reducing the creditworthiness of affected firms when applying for bank loans (Baltas, Fiordelisi, and Mare 2022; Gan 2007). In the empirical analysis, we find that banks raise loan spreads for portfolio companies in disaster-affected areas.

Academic research has shown that the enactment of constituency statutes, which mitigate conflicts between shareholders and stakeholders, enables firms to adopt more stakeholder-friendly policies, enhancing innovation (Flammer and Kacperczyk 2016), reducing borrowing costs (Gao, Li, and Ma 2021) and minimizing earnings management (Ni 2020). Thus, we anticipate that portfolio companies operating in states with stakeholder-oriented statutes may benefit VCs by mitigating the adverse effects caused by natural disasters. Consistent with this hypothesis, we find a positive impact of constituency statutes on the relationship between natural disasters and VC financing decisions.

The COVID-19 pandemic, which began in 2020, posed significant challenges to the economy, similar to natural disasters, by introducing uncertainty into financial markets. Several studies examine the stock market's response to pandemics, especially COVID-19, noting its negative effect on stock returns (Javadi and Masum 2021). Additionally, research highlights operational difficulties caused by pandemics (Ivanov 2020), which further burden startups already impacted by natural disasters. Our extended analysis to 2023, including interactions between COVID-19 and natural disaster damages, shows a compounding effect of COVID-19 and natural disasters could further impede VC financing decisions.

Finally, we document a possible beneficial effect of natural disasters from the perspective of VC investment strategy. Previous studies have highlighted the positive effects of weather-related natural disasters on innovation. Miao and Popp (2014) find that disasters encourage disaster-related patent activities, suggesting that such events can drive innovation to mitigate future risks. They argue that natural disasters inspire technological advancements, such as earthquake detection or drought resistance. Environmentally responsible VCs, with expertise in fostering innovation, may increase investments in disaster-affected portfolio companies to promote green innovation. Aligning with this conjecture, our empirical evidence shows that portfolio companies in disaster zones are more likely to receive funding from green VCs, supporting the notion that natural disasters can catalyze environmentally responsible innovation.[6]

Our paper makes incremental contributions to several strands of literature. First, we extend the emerging body of empirical research that examines the economic and financial consequences of natural disasters. Prior studies have documented how natural disasters hinder corporate financial performance (Hsu et al. 2018; Rehse et al. 2019), influence corporate financial policies (Bernile, Bhagwat, and Rau 2017; Dessaint and Matray 2017), affect capital market participation for institutional investors (Alok, Kumar, and Wermers 2020; Krueger, Sautner, and Starks 2020), impact multinational firms' foreign direct investments (e.g., Oh and Oetzel 2011), and suppress corporate innovation (Miao and Popp 2014). We diverge from this literature by demonstrating that natural disasters can also hinder the financing activities of VCs, a crucial group of capital market participants, and a powerful engine for innovation and economic growth. This finding underscores the need for policymakers to consider the broader economic effects of natural disasters. Additionally, our results on the influence of natural disasters on VC investment sizes corroborate findings from studies in other sectors (e.g., Wang 2023; Alok, Kumar, and Wermers 2020; Akter, Cumming, and Ji 2023; Collier et al. 2024). For instance, Alok, Kumar, and Wermers (2020) report that mutual fund portfolios in disaster zones experience a 1.5% decline in the valuation of each stock, suggesting that fund managers may overreact to disaster risks, leading to downward pressure on the valuation of firms sold by managers. Do, Phan, and Nguyen (2023) find that adverse climate events reduce bank stability, as total deposits and equity become more volatile. Finally, Collier et al. (2024) document that Hurricane Harvey caused a 97% increase in impaired loans for firms compared to pre-Harvey levels.

Second, our study relates to the body of literature investigating the determinants of VC investments (Tian, Wang, and Ye 2023; Shuwaikh et al. 2023; Bianchini and Croce 2022; Chircop, Johan, and Tarsalewska 2020; Iliev and Lowry 2020; Colombo, D'Adda, and Quas 2019; Ning, Wang, and Yu 2015). For example, Tian, Wang, and Ye (2023) find that political uncertainty, particularly gubernatorial elections, reduces VC financing activities. In this context, we contribute to this literature by examining how VCs respond to natural disasters.

Finally, our study contributes to the growing body of research on environmentally responsible capital market participants (Barber, Morse, and Yasuda 2021; Flammer 2021; Geczy et al. 2021; Pástor, Stambaugh, and Taylor 2021; Mansouri and Momtaz 2022). We provide new evidence that climate catastrophes can spur investment in green ventures aimed at developing disaster-resilient technologies to address the increasing threats posed by climate change and natural disasters.

The rest of the paper is structured as follows. Section 2 provides a description of the data and the construction of key variables. Section 3 presents the empirical methodology and empirical results. Section 4 discusses our further analyses. Section 5 concludes the study.

2 | Data and Sample

2.1 | Sample Selection

VC investment data is sourced from VentureXpert, which provides extensive information on VC portfolio companies, including financing dates, the dollar amount of investments, specific characteristics of portfolio companies (e.g., age, location) and VC exit outcomes (e.g., IPO, trade sales, write-offs). Data on natural disasters in the United States between 1990 and 2019 is collected from the Spatial Hazard Events and Losses Database (SHELDUS), managed by the Center for Emergency Management and Homeland Security at Arizona State University.

To explore the impact of climate-related natural disasters on VC investment decisions, our main explanatory variable captures the magnitude of damage caused by natural disasters. Specifically, we calculate the aggregate financial loss per state in a given quarter, incorporating damages from all disasters within the state during that period. Following Barrot and Sauvagnat (2016) and Ouazad and Kahn (2022), we focus on disasters that result in significant financial losses—those exceeding $1 billion within a 31-day period between 1990 and 2019. According to this criterion, we identify 47 major disasters across various states during the sample period. Climatological data, including temperature and precipitation, is sourced from the PRISM Climate Group, managed by Oregon State University. After excluding missing data, we match information from different sources based on the headquarters locations of portfolio companies. For quarters without VC investments, we assign a value of zero. The final sample comprises 323,885 firm-quarter observations from 1990 to 2019. A detailed list of disasters is provided in Table A1.

2.2 | Variable Construction

Our dependent variables measure the propensity of VC investments. Following prior research (e.g., Hain, Johan, and Wang 2016; Chircop, Johan, and Tarsalewska 2020; Shuwaikh et al. 2023), we construct three alternative measures to capture investment propensity on a quarterly basis. The first measure, $\textit{Financing amount}_{j,t}$, is the natural logarithm of one plus the dollar value of total VC investments (in millions of dollars) received by company j in time t. This proxy reflects VCs' investment intentions. The second measure, $\textit{VC syndicate}_{j,t}$, is the natural logarithm of one plus the number of VC investors in a syndicate investing in company j in time t. Prior literature emphasizes that the number of investors significantly influences investment propensity, as syndicates help spread investment risk (e.g., Lockett and Wright 2001; Hoenen et al. 2014). As an additional measure, we employ the average amount of investment a VC firm makes in a portfolio company ($\textit{Avg. Financing amount}_{j,t}$), which is defined as the natural logarithm of one plus the average amount of investment (in $millions) per VC in company j in time t (Cumming and Dai 2011; Humphery-Jenner and Suchard 2013).

As observed in Table A1, the financial loss from the 47 most significant natural disasters in the United States ranges from $1 billion to $125 billion. Using a dummy variable to proxy for disaster damage would fail to capture the significant variation in financial loss. A more accurate measure involves normalizing financial loss by state GDP. This approach facilitates meaningful comparisons of the economic impact of disasters relative to state economic size and provides clearer insights into how disasters affect VC investment decisions. Therefore, our main proxy for disaster-related financial loss is $\textit{Damage ratio}_{it}$, which is the aggregate personal and property damage from natural disasters in state i in quarter t, scaled by the annual state GDP from the prior fiscal year.

Given the delayed effects disasters may have on corporate financing activities, we also construct three lagged versions of the damage ratio, $\textit{L. Damage ratio}_{it}$, $\textit{L2. Damage ratio}_{it}$ and $\textit{L3. Damage ratio}_{it}$. These lagged damage ratios are calculated in the same way as our main variable of interest, but they denote, respectively, the financial loss owing to natural disasters in state i resulting from disasters that occurred one, two and three quarters before the quarter in which we examine their impact on VCs (quarter t). In addition, for a robustness check, we create an indicator variable to capture the effect of these natural disasters that cause the most severe financial damage. The dummy variable, $\textit{Disaster}_{it}$, takes on a value of 1 if at least one of the 47 disasters occurred in state i in quarter t, and 0 otherwise.

We further employ a vector of company-specific characteristics obtained from Thomson One and Compustat as control variables. Given the data limitations for private firms, we follow previous studies to use financial performance at the industry level for portfolio companies (Gompers 1995). Industry is defined according to the 3-digit SIC code. Specifically, we include *Tobin Q, Cashflow, Sales growth* and *R&D* as financial variables. The startup's age (*Age*), the difference between the VC financing year and the company's founding year, is calculated at the portfolio company level. State-level control variables, such as annual GDP and income per capita, are collected from the US Bureau of Economic Analysis (BEA). Additionally, state-level temperature and precipitation data are included as proxies for climatological conditions. Detailed variable definitions are presented in Table B1. To account for unobserved heterogeneity across time, industries, and states, we include year-quarter, state and industry fixed effects.

2.3 | Descriptive Statistics

Panel A of Table 1 reports descriptive statistics for the entire sample. On average, portfolio companies receive $0.231 million from VCs, with 0.168 VCs 0.168 VCs investing per quarter. The mean value of each VC's investment is $0.168 million per quarter. The average damage ratio is approximately $0.021 million. Regarding environmental conditions, the average quarterly temperature across US states is 56.87 °F, and the average Standardized Precipitation Index[7] (SPI) is 0.18. In Panel B of Table 1, we compare VC financing decisions between disaster-affected and non-affected states. The affected group includes firm-quarters in the four quarters following a major natural disaster, while all others form the non-affected group. We find that VCs significantly reduce their investment amounts and are less likely to invest in disaster-affected portfolio companies during the four quarters following the disaster, compared to portfolio companies in unaffected areas. The differences in means are statistically significant at the 1% or 5% level, supporting our hypothesis that natural disasters negatively impact VC financing decisions.

Before moving on to our multivariate regression analysis, we review the correlation matrix for our main variables. The correlation matrix is presented in Table 2. The results indicate no significant concerns regarding multicollinearity, suggesting that our subsequent regression analyses are unlikely to be affected by this issue[8].

3 | Empirical Results

3.1 | Baseline Analysis

Our first step is to investigate how natural disasters influence VCs' investment decisions. We analyze 323,885 quarterly observations for US startups from 1990 to 2019. Specifically, we estimate the following model:

$$\begin{aligned} VC\ investment_{jt} = {} & \beta_1 \bullet Damage\ ratio_{it} + \beta_2 \\ & \bullet L.\ Damage\ ratio_{it} \\ & + \beta_3 \bullet L2.\ Damage\ ratio_{it} \\ & + \beta_4 \bullet L3.\ Damage\ ratio_{it} + \beta_5 \\ & \bullet Controls_{jt} + Year - Quarter\ FE \\ & + Industry\ FE + State\ FE + \varepsilon_{jt}. \end{aligned} \tag{1}$$

Our baseline results on the relationship between natural disasters and VC investment decisions are presented in Table 3. All results are derived from panel data multidimensional fixed-effects linear regressions. We employ three alternative proxies to measure VC investment decisions, as outlined in Section 2.2. The dependent variables are *Financing amount* in columns (1) and (2), *VC syndicate* in columns (3) and (4), and *Avg. Financing amount* in columns (5) and (6). To further capture the unobserved company characteristics, as a robustness check, we

TABLE 1 | Descriptive statistics.

Panel A Descriptive statistics						
Variables	**Obs.**	**Mean**	**Median**	**SD**	**P25**	**P75**
Financing amount	323,885	0.231	0.000	0.712	0.000	0.000
VC syndicate	323,885	0.168	0.000	0.439	0.000	0.000
Avg. Financing amount	323,885	0.168	0.000	0.522	0.000	0.000
Damage ratio	323,885	0.021	0.001	0.245	0.000	0.004
Tobin Q	323,885	0.405	0.108	1.556	0.035	0.338
Cashflow	323,885	−0.001	−0.002	0.011	−0.004	−0.001
Sales growth	323,885	0.013	0.002	0.043	0.001	0.004
Age	323,885	2.021	1.946	0.769	1.386	2.485
R&D	323,885	0.001	0.001	0.156	0.001	0.002
State GDP (billion $)	323,885	0.949	0.660	0.736	0.315	1.523
Precipitation	323,885	0.177	0.110	0.614	−0.183	0.610
Temperature	323,885	56.871	60.370	12.365	44.363	70.460
Income per capita (real, thousand $)	323,885	36.604	38.223	8.131	31.206	42.953

Panel B Univariate analysis					
	Nonaffected		**Affected**		
Variables	**Obs.**	**Mean**	**Obs.**	**Mean**	**Diff. in Means**
Financing amount	299,973	0.232	23,912	0.213	−0.019***
VC syndicate	299,973	0.168	23,912	0.162	−0.006**
Avg. Financing amount	299,973	0.169	23,912	0.157	−0.012***

Note: This table reports summary statistics (the number of observations, mean, median, standard deviation, P25 and P75) for all variables. The sample covers the period of 1990–2019. All variables are defined in Appendix B.

TABLE 2 | Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Damage ratio	1									
(2) Tobin Q	−0.007***	1								
(3) Cashflow	0.009***	−0.275***	1							
(4) Sales growth	−0.003*	−0.005***	−0.015***	1						
(5) Age	0.013***	−0.003*	0.014***	−0.006***	1					
(6) State GDP	−0.028***	0.293***	−0.241***	0.017***	0.059***	1				
(7) Precipitation	0.006***	−0.035***	−0.020***	−0.002	0.025***	−0.019***	1			
(8) Temperature	0.012***	−0.015***	−0.172***	0.007***	−0.003*	0.060***	0.139***	1		
(9) Income per capita	0.057***	0.205***	−0.197***	0.007***	0.041***	0.381***	0.047***	0.069***	1	
(10) R&D	0.000	0.005***	−0.003*	0.000	−0.001	0.006***	0.005***	0.001	0.006***	1

Note: This table reports the correlation coefficients between our main variables. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

include company fixed effects and report the results in columns (2), (4) and (6).

The coefficients for the damage ratios, lagged by two quarters, are consistently negative and statistically significant at levels ranging from 10% to 1%, indicating a substantial negative impact of natural disasters on VC investment decisions in entrepreneurial firms. The results also demonstrate economic significance. For example, in column (1), a one-standard-deviation increase in the damage ratio corresponds, on average, to a 14.74% decline in VC investments in startups. This effect is sizable, as the percentage drop translates to an approximate $200,000 reduction in US dollar value on average. We interpret this as the first piece of empirical evidence supporting our hypothesis that natural disasters significantly hinder VC investments in startups located in disaster-affected zones.

Regarding the control variables, we find that younger companies are more likely to receive VC funding. The positive and significant coefficient for *Cash flow* suggests that startups generating higher cash flows are better able to signal their quality, thereby attracting more investment from VCs. Additionally, we observe evidence of a positive influence of state-level macroeconomic conditions on VC investment decisions, while climate-related risks have a negative impact on these decisions.

3.2 | Propensity Score Matching-Difference-in-Differences (PSM-DiD) Estimation

To better establish causal pathways and address potential selection biases, we apply the PSM procedure, followed by a DiD estimation (Rosenbaum and Rubin 1983; Bertrand, Duflo, and Mullainathan 2004). This approach aims to provide more robust estimates of the impact of natural disasters on VC investment decisions. First, we implement the PSM procedure by using a major disaster dummy variable (representing one of the 47 disasters) to match companies in states affected by major natural disasters with those in unaffected states. We employ one-to-one nearest neighbor matching each year, using a vector of company characteristics for non-replacement matching and the same control variables as in the baseline model. After matching, we conduct the DiD estimation on the post-matching sample.

In unreported tests, we conducted matched pair *t*-tests using matching variables as the dependent variables for the matched companies. The results indicate no significant differences between the treatment and control groups, suggesting that the PSM procedure successfully eliminated differences between the two groups.

For the DiD estimation, we examine VC investments in startups four quarters before and four quarters after the 47 natural disasters. The following regression equation is estimated:

$$\begin{aligned} VC\ investment_{jt} = {} & \beta_1 \cdot Treat_{it} * Post_{it} + \beta_2 \cdot Treat_{it} + \beta_3 \\ & \cdot Post_{it} + \beta_4 \cdot Controls_{jt} + Year \\ & - Quarter\ FE + Industry\ FE \\ & + State\ FE + \varepsilon_{jt} \end{aligned} \tag{2}$$

TABLE 3 | Natural disasters and VC investment decisions.

	Financing amount		VC syndicate		Avg. Financing amount	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Damage ratio	0.226	0.314	0.357	0.184	0.058	0.113
	(0.663)	(0.550)	(0.384)	(0.665)	(0.835)	(0.688)
L. Damage ratio	0.331	0.504	−0.040	−0.058	0.357	0.472
	(0.424)	(0.201)	(0.879)	(0.823)	(0.290)	(0.129)
L2. Damage ratio	−0.904***	−0.638**	−0.405*	−0.419*	−0.713***	−0.529***
	(0.001)	(0.012)	(0.099)	(0.081)	(0.000)	(0.002)
L3. Damage ratio	−0.290	−0.264	0.201	−0.044	−0.359	−0.358
	(0.613)	(0.642)	(0.684)	(0.929)	(0.390)	(0.382)
Tobin Q	0.002	0.000***	0.000	0.000***	0.001	0.000**
	(0.132)	(0.008)	(0.400)	(0.007)	(0.296)	(0.020)
Cashflow	0.531***	0.005***	0.373***	0.003***	0.237*	0.003**
	(0.003)	(0.004)	(0.001)	(0.005)	(0.068)	(0.036)
Sales growth	0.030	0.000	0.028**	0.000	0.016	0.000
	(0.101)	(0.552)	(0.020)	(0.187)	(0.225)	(0.791)
Age	−0.088***	−0.048***	−0.064***	−0.028***	−0.061***	−0.046***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D	0.011	0.000	0.012*	0.000*	0.007	0.000
	(0.235)	(0.260)	(0.087)	(0.074)	(0.287)	(0.307)
State GDP	0.042***	0.000***	0.002	0.000***	0.035***	0.000***
	(0.000)	(0.000)	(0.747)	(0.000)	(0.000)	(0.000)
Precipitation	−0.008***	−0.007**	−0.004**	−0.004**	−0.005**	−0.004**
	(0.008)	(0.018)	(0.021)	(0.032)	(0.013)	(0.042)
Temperature	−0.001***	−0.003***	−0.001***	−0.002***	−0.000***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)
Income per capita	0.009***	0.000***	0.005**	0.000***	0.007***	0.000***
	(0.007)	(0.000)	(0.032)	(0.000)	(0.005)	(0.000)
Intercept	−0.060	−1.017***	0.362***	−0.489***	−0.036	−0.747***
	(0.483)	(0.000)	(0.000)	(0.000)	(0.557)	(0.000)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes
Obs.	323,885	323,885	323,885	323,885	323,885	323,885
Adj. R-sq	0.022	0.052	0.025	0.065	0.018	0.051

Note: This table reports the results of the following pooled OLS regression run at the firm-year-quarter level: $VC\ investment_{jt} = \beta_1 \bullet Damage\ ratio_{it} + \beta_2 \bullet L.Damage\ ratio_{it} + \beta_3 \bullet L2.Damage\ ratio_{it} + \beta_4 \bullet L3.Damage\ ratio_{it} + \beta_5 \bullet Controls_{jt} + Year\!-\!quarter\ FE + Industry\ FE + State\ FE + \varepsilon_{jt}$. are various proxies for $VC_{investment}$ of firm j in quarter t: *Financing amount*, *VC syndicate*, and *Avg. Financing amount*. *Financing amount* is the natural logarithm of 1 plus the total amount of VC investments (in $millions) received by firm j at quarter t. *VC syndicate* is the natural logarithm of 1 plus the number of investors in a VC syndicate in firm j at quarter t. *Avg. Financing amount* is the natural logarithm of 1 plus the average VC investment amount per VC investor in firm j at quarter t. The explanatory variables are *Damage ratio*$_{it}$, which is the total damage of all natural disasters in state i during quarter t divided by the annual state GDP in year $t-1$, and the lagged (three quarters) damage ratios. All variables are defined in Appendix B. All firm-characteristic variables are as of the end of the prior year. Year-Quarter, Industry, and State fixed effects are included in Columns (1), (3) and (5), whereas Year-Quarter, and Firm fixed effects are included in Columns (2), (4), and (6). We report coefficient estimates with p-values in parentheses below. p-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

where the VC-related variables, control variables, and fixed effects are the same as those in Equation (1). *Treat* is a dummy variable that equals 1 if a startup's headquarters is located in a state affected by a major disaster, and 0 otherwise. *Post* is a dummy variable equal to 1 for the four quarters following a disaster, and 0 otherwise. The key variable of interest is the interaction term *Treat*Post*. which captures the incremental change in VC investments for companies in disaster-affected areas relative to control companies. A negative coefficient indicates that, following a disaster, companies in affected areas receive less VC funding (or experience less increase) compared to those in unaffected areas. Table 4 reports the results of PSM-DiD estimation.

The coefficients for *Treat*Post* are negative and statistically significant at conventional levels for most quarters after the disasters, confirming our baseline results that natural disasters negatively impact VC financing decisions. Additionally, some studies suggest that bank loans and VC financing are substitutes (Winton and Yerramilli 2008; de Bettignies and Brander 2007). Given that natural disasters introduce both physical and transitional climate risks, bank debt financing in disaster areas may also be affected, potentially influencing VC financing decisions. Heo (2022) reveals that climate change leads to bank fragility and introduces systemic risk. To ensure our results are not influenced by the state level financial stability, we follow previous studies and use loan losses as a proxy for banks' financial stability (e.g., Tölö and Virén 2021). Specifically, we collect data on net loan losses to average total loans at the state level from the *Federal Reserve Bank of St. Louis* and include this variable in the PSM process. Panel B of Table 4 reports these results. We consistently find that natural disasters discourage VCs from making investments, as the coefficients on *Treat*Post* are negative and significant at conventional levels from the second to the fourth quarters. Overall, Overall, we interpret these findings as robust evidence of a causal relationship between natural disasters and VC investment decisions.

3.3 | The VC Exit Mechanisms

To empirically test the impact of natural disasters on VC exit mechanisms, we employ panel probit regression. We consider an IPO the most desirable and successful exit for VCs due to its significant valuation premium (Cumming 2008; Cumming and Johan 2008; Reuer and Ragozzino 2012; Chemmanur, Signori, and Vismara 2023). Specifically, the dependent variable, *IPO*, is a binary variable taking the value of 1 if a VC successfully exits via IPO in a specific year, and 0 otherwise. Additionally, as prior studies recognize trade sales through mergers and acquisitions as an alternative successful exit strategy, we construct an **All exits** variable, which equals 1 if the VC exits through either IPO or trade sales, and 0 if the venture ends in failure (e.g., liquidation). We include the same control variables as in the baseline model, along with year-quarter, industry and state fixed effects. Table 5 shows the results of the probit regression.

The results unequivocally show that in the second quarter following natural disasters, the likelihood of successfully cashing out from portfolio firms is significantly reduced. Pertaining to the marginal effect, a one-standard-deviation increase in the damage ratio corresponds to a 54 basis points drop in the probability of successful exit by all means.

For robustness, we apply the PSM-DiD methodology to VC exits, following the approach outlined earlier, with results shown in Panel A of Table 6. The estimates for *Treat*Post* are negative and statistically significant during the second and third quarters after the disasters, regardless of whether success is measured by IPO alone or by including trade sales. In Panel B, we account for state-level financial stability by including net loan losses to average total loans at the state level in the PSM process, as described in Section 3.2. The coefficients for *Treat*Post* remain significant at the 1% or 5% levels across the four quarters following a disaster. These findings reinforce the causal relationship between natural disasters and the likelihood of successful exits for VC investors. The results indicate that the difficulty of achieving successful exits is significantly greater for portfolio companies located in disaster-affected areas than for those in the control group during the four quarters following the climate disasters.

3.4 | Survival Analysis for VC Exits

It is important to note that probit regression does not account for the duration of VC exits (IPO or trade sales), potentially leading to estimation bias. For example, probit models treat exits occurring in the first and fourth quarters equally, which may not reflect reality. To address this, we employ the Cox proportional hazards model (count process), which allows for time-varying covariates and multiple measurement intervals, to analyze the timing of exits (David 1972; Andersen and Gill 1982). The Cox model estimates the conditional probability of an event occurring, given that it has not yet occurred. Positive (negative) coefficients indicate that the covariates increase (decrease) the likelihood of the event.

In this study, the hazard event refers to a VC cashing out of a portfolio firm via IPO—the most preferred exit option due to its valuation premium. The dependent variable, *Success IPO*, represents the duration it takes for a VC-backed firm to go public, measured as the number of days between the initial VC investment and the IPO listing date. The duration is measured as the days between the initial date a startup receives VC sponsorship and the IPO listing date. Given the specific nature of the Cox proportional hazards model, we employ the indicator variable, *Disaster*, as the explanatory variable[9]. We include the same control variables as in the baseline model, along with year-quarter, industry and state fixed effects. To ensure robustness, we conduct both cross-sectional and panel Cox hazard regression analyses. Table 7 presents the results

The results from cross-sectional regression being presented in column (1) and those from panel regression being reported in column (2). The findings are consistent with the probit model results. The coefficients of our variable of interest, *Disaster*, are negative and statistically significant at the 1% level in both specifications, indicating that natural disasters significantly delay VC exits via IPO for their portfolio companies. These results further highlight the detrimental impact of climate disasters on VC investments.

4 | Further Analysis

4.1 | Tangibility

Next, we conduct further analysis to explore the role of tangibility in the relationship between natural disasters and VC

TABLE 4 | Natural disasters and VC investment decisions (PSM-DiD analysis).

Panel A: Basic PSM-DiD

	Financing amount				VC syndicate				Avg. Financing amount			
	(1) Q1	**(2) Q2**	**(3) Q3**	**(4) Q4**	**(5) Q1**	**(6) Q2**	**(7) Q3**	**(8) Q4**	**(9) Q1**	**(10) Q2**	**(11) Q3**	**(12) Q4**
Treat	0.003	0.006	0.005	0.006	0.005	0.006	0.005	0.005	0.004	0.006	0.006	0.007
	(0.679)	(0.369)	(0.431)	(0.405)	(0.347)	(0.111)	(0.194)	(0.252)	(0.420)	(0.217)	(0.231)	(0.197)
Post	−0.008	0.003	−0.002	−0.002	0.002	0.001	−0.002	−0.000	−0.014	−0.006	−0.009**	−0.007**
	(0.476)	(0.581)	(0.695)	(0.549)	(0.838)	(0.871)	(0.405)	(0.964)	(0.104)	(0.225)	(0.041)	(0.023)
Treat*Post	0.003	−0.023**	−0.024***	−0.027***	0.005	−0.010	−0.009*	−0.009*	0.001	−0.014**	−0.016***	−0.019***
	(0.828)	(0.018)	(0.000)	(0.000)	(0.608)	(0.186)	(0.096)	(0.085)	(0.948)	(0.030)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	62,749	71,603	83,305	93,301	62,749	71,603	83,305	93,301	62,749	71,603	83,305	93,301
Adj. R-sq	0.022	0.022	0.023	0.023	0.026	0.026	0.027	0.027	0.020	0.020	0.020	0.020

Panel B: PSM-DiD (matched with state-level financial stability in addition)

	Financing amount				VC syndicate				Avg. financing amount			
	(1) Q1	**(2) Q2**	**(3) Q3**	**(4) Q4**	**(5) Q1**	**(6) Q2**	**(7) Q3**	**(8) Q4**	**(9) Q1**	**(10) Q2**	**(11) Q3**	**(12) Q4**
Treat	0.002	0.005	0.005	0.005	0.005	0.006	0.005	0.005	0.003	0.006	0.006	0.006
	(0.757)	(0.430)	(0.467)	(0.455)	(0.349)	(0.130)	(0.186)	(0.242)	(0.479)	(0.256)	(0.249)	(0.222)
Post	−0.008	0.006	0.003	0.006	0.007	0.008	0.004	0.003	−0.007	−0.000	−0.003	0.000
	(0.598)	(0.580)	(0.698)	(0.301)	(0.487)	(0.174)	(0.466)	(0.479)	(0.517)	(0.988)	(0.661)	(0.953)
Treat*Post	−0.001	−0.022**	−0.017**	−0.014***	−0.007	−0.015**	−0.007*	−0.005*	−0.003	−0.016**	−0.014***	−0.012***
	(0.968)	(0.043)	(0.014)	(0.006)	(0.630)	(0.035)	(0.089)	(0.079)	(0.783)	(0.035)	(0.010)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 4 | (Continued)

Panel B: PSM-DiD (matched with state-level financial stability in addition)

	Financing amount				VC syndicate				Avg. financing amount			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q1	(6) Q2	(7) Q3	(8) Q4	(9) Q1	(10) Q2	(11) Q3	(12) Q4
Obs.	62,749	71,603	83,305	93,301	62,749	71,603	83,305	93,301	62,749	71,603	83,305	93,301
Adj. R-sq	0.027	0.027	0.027	0.027	0.031	0.031	0.031	0.031	0.024	0.025	0.024	0.024

Note: This table reports the results for the impact of natural disasters on VC investment using a difference-in-differences analysis following a propensity score matching routine (PSM-DiD). The post-matching DiD analysis is performed on a sample of startups receiving VC financing before and after the natural disaster. We estimate the OLS regressions as follows: $VC\ investment_{jt} = \beta_1 \bullet Treat_{it} * Post_{it} + \beta_2 \bullet Treat_{it} + \beta_3 \bullet Post_{it} + \beta_4 \bullet Controls_{jt} + Year\text{–}Quarter\ FE + Industry\ FE + State\ FE + \varepsilon_{jt}$. The regression is run at the firm-year-quarter level. From Columns (1) to (4), the dependent variables are *Financing amount*. The dependent variables from Column (5) to (8) are *VC syndicate*. The dependent variables from Column (9) to (12) are *Avg. Financing amount*. *Treat* is a dummy variable that takes the value of 1 for firms that are located in states affected by at least one of the 47 natural disasters, and 0 for matched firms that are not located in such states. *Post* is a dummy variable that takes the value of 1 for the quarters post natural disasters, and 0 otherwise. Q1–Q4 denotes the four quarters following the occurrence of a natural disaster. All variables are defined in Appendix B. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p*-values in parentheses below. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 5 | Natural disasters and the VC exit mechanisms.

	IPO **(1)**	***All exits*** **(2)**
Damage ratio	30.474	20.824
	(0.314)	(0.755)
L. Damage ratio	−6.374	15.405
	(0.945)	(0.482)
L2. Damage ratio	−65.358**	−41.536**
	(0.038)	(0.041)
L3. Damage ratio	−11.125	−10.615
	(0.579)	(0.350)
Controls	Yes	Yes
Year-Quarter FE	Yes	Yes
State FE	Yes	Yes
Industry FE	Yes	Yes
Obs.	83,873	83,873
Pseudo R-sq	0.134	0.036

Note: This table reports the results of the following probit model performed at the firm-year-quarter level: $Exit_{jt} = \beta_1 \bullet Damage\ ratio_{it} + \beta_2 \bullet L.Damage\ ratio_{it} + \beta_3 \bullet L2.Damage\ ratio_{it} + \beta_4 \bullet L3.Damage\ ratio_{it} + \beta_5 \bullet Controls_{jt} + Year\text{–}Quarter\ FE + Industry\ FE + State\ FE + \varepsilon_{jt}$. choices of VC for their portfolio firms. *IPO* is an indicator variable that equals 1 if the exit choice is IPO, and 0 otherwise. All exits is a dummy variable that equals 1 if venture capitalists successfully exit from their portfolio firms via by IPO or trade sales (acquisitions), and 0 if the portfolio firms are liquidated. All variables are defined in Appendix B. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

investment decisions. Intuitively, companies with a higher proportion of fixed assets are more vulnerable to losses during natural disasters and face greater disaster-related risks. Consequently, VCs may adjust their investment strategies based on the proportion of fixed assets in their portfolio startups. To investigate this, we divide the sample into two subsamples based on the ratio of fixed assets to total assets at the industry level and re-estimate our baseline model. Specifically, the first group consists of startups in industries with a tangible assets ratio below the median, while the second group comprises startups in industries with a tangible assets ratio above the median. We aim to assess whether there is a difference in VC investments between low- and high-tangibility firms following natural disasters. Table 8 presents the results.

The empirical results confirm our conjecture. Startups in industries with a higher proportion of tangible assets (and thus higher exposure to disaster risks) experience significant reductions in VC investments during the second and third quarters following a disaster. Conversely, no significant effect is observed for startups in industries with a low ratio of tangible assets, suggesting lower risk exposure to natural disasters.

4.2 | Industry Analysis

Building on the analysis of tangible asset levels, the impact of natural disasters on VC investment decisions may vary across

TABLE 6 | Natural disasters and the VC exit mechanisms (PSM-DiD).

Panel A: Basic PSM-DiD

	IPO				All exits			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q1	(6) Q2	(7) Q3	(8) Q4
Treat	0.031	0.017	0.080	0.128	0.075	0.067	0.099	0.097
	(0.779)	(0.867)	(0.418)	(0.175)	(0.282)	(0.311)	(0.119)	(0.115)
Post	0.071	0.236*	0.205*	0.198**	0.163	0.286***	0.280***	0.267***
	(0.698)	(0.082)	(0.076)	(0.037)	(0.192)	(0.002)	(0.000)	(0.000)
Treat*Post	−0.436*	−0.423***	−0.296**	−0.176*	−0.216	−0.261***	−0.185**	−0.145*
	(0.073)	(0.004)	(0.012)	(0.097)	(0.150)	(0.007)	(0.022)	(0.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,390	18,089	21,556	24,565	15,390	18,089	21,556	24,565
Pseudo R-sq	0.192	0.174	0.164	0.162	0.102	0.089	0.079	0.078

Panel B: PSM-DiD (matched with state-level financial stability in addition)

	IPO				All exits			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q1	(6) Q2	(7) Q3	(8) Q4
Treat	0.035*	0.034	0.051**	0.059**	0.051	0.060*	0.083*	0.086*
	(0.050)	(0.101)	(0.033)	(0.039)	(0.159)	(0.086)	(0.068)	(0.094)
Post	0.104	0.119*	0.111*	0.117**	0.143	0.217*	0.294***	0.283***
	(0.159)	(0.098)	(0.060)	(0.034)	(0.137)	(0.063)	(0.000)	(0.000)
Treat*Post	−0.177***	−0.209***	−0.149***	−0.087***	−0.188**	−0.266***	−0.191***	−0.148***
	(0.003)	(0.002)	(0.004)	(0.009)	(0.024)	(0.001)	(0.002)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,390	18,089	21,556	24,565	15,390	18,089	21,556	24,565
Pseudo R-sq	0.192	0.174	0.164	0.162	0.102	0.089	0.079	0.078

Note: This table reports the results for the impact of natural disasters on VC exits using a difference-in-differences analysis following a propensity score matching routine (PSM-DiD). The post-matching DiD analysis is performed on a sample of startups receiving VC financing before and after the natural disaster. We estimate the probit model as follows: $Exit_{jt} = \beta_1 \bullet Treat_{it} {*} Post_{it} + \beta_2 \bullet Treat_{it} + \beta_3 \bullet Post_{it} + \beta_4 \bullet Controls_{jt} + Year\text{−}Quarter\ FE + Industry\ FE + State\ FE + \varepsilon_{jt}$. The dependent variable is the exit choices of VC for their portfolio firms. *IPO* is an indicator variable that equals 1 if the exit choice is IPO, and 0 otherwise. *All exit* is a dummy variable that equals 1 if venture capitalists successfully exit from their portfolio firms via by IPO or trade sales (acquisitions), and 0 if the portfolio firms are liquidated. *Treat* is a dummy variable that takes the value of 1 for firms that are located in states affected by at least one of the 47 natural disasters, and 0 for matched firms that are not located in such states. *Post* is a dummy variable that takes the value of 1 for the quarters post natural disasters, and 0 otherwise. Q1–Q4 denotes the four quarters following the occurrence of a natural disaster. All variables are defined in Appendix B. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

industries due to differences in tangible asset proportions and associated risk exposure. To examine this, we classify the sample into five groups using the Fama-French 5 industry classification and conduct separate regression analyses for each group[10]. The results, presented in Table 9, reveal that the detrimental effect of natural disasters on VC investments is primarily driven by two industry groups with relatively high levels of tangible assets. Specifically, the negative impact is most pronounced in industries related to consumer durables, non-durables, wholesale, retail, and certain services (e.g., laundries, repair shops). The results in column (1) show an immediate negative impact in these industries. In contrast, firms in manufacturing, energy and utilities experience a delayed impact, with significant reductions in VC investments emerging in the second quarter following the disaster. These findings are intuitive, as the production cycles of consumer durables, non-durables, wholesale, retail, and certain services are typically shorter than those of manufacturing, energy, and utilities firms[11].

4.3 | Natural Disaster Types

In the baseline results, we consider damages caused by overall disasters. However, there are different types of disasters which could exert differential impact on VC investment decisions. To provide further insights into how VCs react to different disaster events, we consider different types of disasters in the analysis. Specifically, we classify the natural disasters into five groups, hurricane/typhoon, flood, winter storm, wildfire and earthquake, respectively. Table 10 presents the results. Overall, our findings indicate that all types of natural disasters negatively influence VC investment decisions, with wildfire and earthquake exerting the most pronouncing impact. Moreover, we find some disaster events could impose persistent adverse impacts on VC financing activities[12]. For example, the occurrence of an earthquake leads VCs to reduce investment amount in portfolio companies during the disaster event quarter, as well as in the two subsequent quarters. This is consistent with the notion that earthquakes in the US are becoming more costly, especially in California[13].

TABLE 7 | The impact of natural disasters on the speed of VC exits through IPO.

	Cross-sectional Success IPO (1)	Panel Success IPO (2)
Disaster	−1.185***	−0.237***
	(0.000)	(0.000)
Controls	Yes	Yes
Year-Quarter FE	Yes	Yes
State FE	Yes	Yes
Industry FE	Yes	Yes
Obs.	12,735	174,818
Pseudo R-sq	0.395	0.498

Note: This table reports the results of the survival analysis using Cox Hazard Model for VC-sponsored entrepreneurial firms to examine the impact if natural disasters on the speed of VC exits through IPO. The dependent variable, *Success IPO*, represents the duration it takes for a VC backed private firm to go public. The duration is measured with the days between the initial date an entrepreneurial firm receiving VC sponsorship and the IPO listing date. We employ the cross-sectional Cox Hazard Model in Column (1), whereas the panel Cox Hazard Model in Column (2). All variables are defined in Appendix B. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively

4.4 | Natural Disaster Risks

Previous studies suggest that natural disasters impose fears on investors' sentiment, thereby affecting their investment decisions. For example, Fiordelisi, Galloppo and Paimanova (2023) report that severer natural disasters induce fears from investors, thereby affecting their investment behavior by investing more in sustainable financial products. Indeed, psychological studies indicate that disasters amplify fears and anxiety for people (Tversky and Kahneman 1974; Västfjäll, Peters, and Slovic 2014). Although our main measure of

TABLE 8 | Tangibility and VC investment decisions.

	Below median			Above median		
	Financing amount (1)	VC syndicate (2)	Avg. Financing amount (3)	Financing amount (4)	VC syndicate (5)	Avg. Financing amount (6)
Damage ratio	−0.457	−0.394	−0.160	−0.119	−0.304	−1.081
	(0.734)	(0.338)	(0.832)	(0.437)	(0.334)	(0.418)
L. Damage ratio	−0.209	−0.630	−0.276	−0.172	−0.364	−1.299
	(0.397)	(0.937)	(0.235)	(0.467)	(0.540)	(0.382)
L2. Damage ratio	−1.382	−0.529	−0.847	−1.029**	−0.179	−1.975***
	(0.756)	(0.732)	(0.524)	(0.025)	(0.390)	(0.004)
L3. Damage ratio	−0.427	−0.697	−0.491	−0.596*	−0.436	−1.310**
	(0.994)	(0.663)	(0.819)	(0.084)	(0.267)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	139,402	139,402	139,402	145,809	145,809	145,809
Adj. R-sq	0.018	0.023	0.015	0.029	0.033	0.025

Note: This table reports the influence of startups' tangibility on the link between natural disasters and VC investment decisions. We split our sample into two groups: the first group is the private firms with tangible assets below the median value and the second group is the private firms with tangible assets above the median value. The dependent variables are various proxies for $VC_{investment}$ of firm *j* in quarter *t*: *Financing amount, VC syndicate*, and *Avg. Financing amount*. The explanatory variables are *Damage ratio*$_{it}$ and the lagged (three quarters) damage ratios. All variables are defined in Appendix B. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 9 | Industry classification and VC investment decisions.

	Consumer Durables, Non-Durables, Wholesale, Retail, and Some Services (Laundries, Repair Shops) (1)	Manufacturing, Energy, and Utilities (2)	Business Equipment, Telephone and Television Transmission (3)	Healthcare, Medical Equipment, and Drugs (4)	Other-Mines, Construction, Building Management, Transportation, Hotels, Business Service, Entertainment, Finance (5)
Financing amount					
Damage ratio	−1.371**	0.249	0.735	−0.959	−0.801
	(0.046)	(0.738)	(0.406)	(0.485)	(0.254)
L. Damage ratio	0.882	−0.593	0.089	2.870	−0.459
	(0.506)	(0.584)	(0.859)	(0.178)	(0.564)
L2. Damage ratio	0.309	−1.031**	−0.375	−1.193	−0.683
	(0.694)	(0.018)	(0.257)	(0.338)	(0.233)
L3. Damage ratio	−2.066	0.376	−0.979	0.171	−1.643
	(0.200)	(0.775)	(0.266)	(0.914)	(0.297)
Controls	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Obs.	22,080	18,051	200,478	58,045	25,231
Adj. R-sq	0.046	0.040	0.034	0.021	0.049

Note: This table reports the influence of industry classification on the link between natural disasters and VC investment decisions. We split our sample into five groups according to the industry classification of startups. The dependent variables are various proxies for $VC_{investment}$ of firm *j* in quarter *t*: *Financing amount*, *VC syndicate*, and *Avg. Financing amount*. The explanatory variables are D*amage ratio*$_{it}$ and the lagged (three quarters) damage ratios. All variables are defined in Appendix B. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

disaster damage ratio can capture fears from investors, this section further investigates how disaster risks affect VC financing decisions.

The Federal Emergency Management Agency (FEMA) works alongside other federal agencies to strengthen the nation's ability to prepare for and respond to disasters. In 2021, FEMA launched hazard risk assessments for 18 types of natural disasters at the county level. We utilize the overall risks scores to examine the impact of portfolio companies' local hazard risks on VC financing decisions. These scores indicate the relative risk of natural disasters in a particular region compared to others. We acquire Zip codes for portfolio companies' headquarters from VentureXpert and match them with Federal Information Processing Standards (FIPS) codes from the US Census to confirm each portfolio companies' county. As FEMA's disaster risk index was first released in 2021 that mainly captures the disaster risk exposure starting from 2017, we therefore perform a subsample analysis from 2017 to 2019 for the disaster risk index. Specifically, we assign the appropriate risk score to each portfolio company using county FIPS codes from 2017 to 2019 in our analysis. Table 11 presents the results. In Column (1), the coefficient on the variable of interest, *Natural disaster risk*, is negative and statistically significant at the 1% level, suggesting that a higher risk of the occurrence of natural disasters at portfolio company's location negatively affect VC financing decisions by reducing investment amount. We obtain similar results in Columns (2) and (3), where we use *VC syndicate* and *Avg. Financing amount* as dependent variables. Thus, the overall findings support our conjecture that fears of natural disasters tend to hinder VC financing, further corroborating our primary hypothesis for a detrimental effect of natural disasters negatively on VC investment decisions.

4.5 | Natural Disasters and Cost of Finance

Our results suggest that natural disasters increase the cost of financing for startups seeking to attract VC investments. Some studies argue that climate-related events, such as disasters, also negatively affect other types of financing. For example, El Ghoul et al. (2023) document that firms exposed to climate risks face higher borrowing costs due to increased leverage. Natural disasters can cause significant damage to corporate assets,

TABLE 10 | Natural disaster types and VC investment decisions.

	Hurricane/Typhoon (1)	Flood (2)	Winter storm (3)	Wildfire (4)	Earthquake (5)
Financing amount					
Disaster type	−0.417	−1.032	−0.027	5.279	−1.650
	(0.406)	(0.591)	(0.995)	(0.439)	(0.108)
L. Disaster type	−0.306	−2.341**	2.735	2.063	−1.311
	(0.266)	(0.017)	(0.603)	(0.456)	(0.261)
L2. Disaster type	−0.780***	1.825	−9.111***	−6.351***	−2.041**
	(0.002)	(0.531)	(0.000)	(0.000)	(0.013)
L3. Disaster type	−1.267	4.209	8.646	−16.307***	−2.348**
	(0.144)	(0.259)	(0.313)	(0.007)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	323,885	323,885	323,885	323,885	323,885
adj. R-sq	0.021	0.021	0.021	0.021	0.021

Note: This table reports the results for the impact of different types of natural disasters on VC investment decisions. Natural disasters are classified into five groups: hurricane/typhoon, flood, winter storm, wildfire, and earthquake respectively. The results for the five types are presented in Columns (1)–(5) respectively. The dependent variable is *Financing amount*, which is the natural logarithm of 1 plus the total amount of VC investments (in $millions) received by firm *j* at quarter *t*. The explanatory variable Disaster type is the damage ratio for different types of disasters, which is the total damage of a certain type of natural disasters in state *i* during quarter t divided by the annual state GDP in year *t*−1, and the lagged (three(three quarters) damage ratios. Disaster types include hurricane/typhoon, flood, winter storm, wildfire and earthquake. All variables are defined in Appendix B. All firm-characteristic variables are as of the end of the prior year. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 11 | Natural disaster risk and VC investment decisions.

	Financing amount (1)	VC syndicate (2)	Avg. Financing amount (3)
Natural disaster risk	−0.003***	−0.002***	−0.002**
	(0.000)	(0.000)	(0.015)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	31,601	31,601	31,601
adj. R-sq	0.021	0.027	0.018

Note: This table reports the results for the impact of natural disaster risk on VC investment decisions. The dependent variables are various proxies for $VC_{investment}$ of firm *j* in quarter *t*: *Financing amount*, *VC syndicate*, and *Avg. Financing amount*. *Financing amount* is the natural logarithm of 1 plus the total amount of VC investments (in $millions) received by firm *j* at quarter *t*. *VC syndicate* is the natural logarithm of 1 plus the number of investors in a VC syndicate in firm *j* at quarter *t*. *Avg. Financing amount* is the natural logarithm of 1 plus the average VC investment amount per VC investor in firm *j* at quarter *t*. The explanatory variable is *Natural disaster risk*, which measures the risk of having natural disasters where the portfolio company locates. All variables are defined in Appendix B. All firm-characteristic variables are as of the end of the prior year. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

reducing creditworthiness and making it more difficult for affected companies to secure bank loans (Baltas, Fiordelisi, and Mare 2022; Gan 2007). Consequently, borrowing costs for companies in disaster-affected areas may rise. However, since VC-backed firms carry a reputational advantage, the impact of natural disasters on their access to debt financing may be negligible. Thus, it remains an empirical question whether natural disasters affect the cost of financing for VC-backed startups.

To explore this, we collect bank loan interest rates from Refinitiv Loan Pricing Corporation (LPC) DealScan and match them with our sample. We follow previous studies to measure loan spreads as the interest rate spread above LIBOR, plus annualized upfront fees (Saunders and Steffen 2011; Schenone 2010; Pagano, Panetta, and Zingales 1998). The variable *Loan spreads* represents the overall cost of bank loans for VC-backed startups and serves as the dependent variable. Table 12 presents the results.

TABLE 12 | Natural disasters and cost of debt.

	Loan spreads (1)
Damage ratio	0.980**
	(0.037)
L. Damage ratio	0.135*
	(0.089)
L2. Damage ratio	0.603
	(0.465)
L3. Damage ratio	0.322
	(0.756)
Control	Yes
Year-Quarter FE	Yes
State FE	Yes
Industry FE	Yes
N	286,799
adj. R-sq	0.014

Note: This table reports the results for the impact of natural disasters on the cost of borrowing in VC-sponsored startups. The dependent variable is loan spreads, measured as the interest rate spreads above LIBOR plus annualized upfront fees The explanatory variables are *Damage ratio*$_{it}$, which is the total damage of all natural disasters in state i during quarter *t* divided by the annual state GDP in year *t*−1, and the lagged (three quarters) damage ratios. All variables are defined in Appendix B. All firm-characteristic variables are as of the end of the prior year. Year-Quarter, Industry, and State fixed effects are included in Columns (1), (3), and (5), whereas Year-Quarter, and Firm fixed effects are included in Columns (2), (4), and (6). We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

The coefficients for *Damage ratio* and *L. Damage ratio* are positive and significant at the 5% and 10% levels, respectively, indicating that banks increase loan spreads for portfolio companies during the disaster quarter and the quarter following a disaster. This finding implies that natural disasters damage corporate assets and reduce the value of collateral, which diminish the creditworthiness of startups. As a result, banks perceive higher risk in lending to disaster-affected startups and charge higher interest rates.

4.6 | Stakeholder Orientation, Natural Disasters and VC Investment Decisions

Non-shareholder constituency statutes, also known as stakeholder statutes, are legal provisions adopted by certain US states that permit or require corporate directors to consider the interests of stakeholders beyond shareholders when making decisions (Ni 2020; Ni, Song, and Yao 2020; Koskinen, Lu, and Nguyen 2024; Adams and Ferreira 2007). These stakeholders may include employees, customers, suppliers, creditors, local communities and environmental considerations, in addition to the customary focus on shareholder interests. Previous studies document that the enactment of constituency statues in US states significantly benefits firms located in such states in a variety of ways (Flammer and Kacperczyk 2016; Koskinen, Lu, and Nguyen 2024; Gao, Li, and Ma 2021; Ni 2020; Ni, Song, and Yao 2020). Flammer and Kacperczyk (2016), for example, find that the adoption of these statutes positively impacts corporate innovation, as firms in stakeholder-oriented states implement more stakeholder-friendly policies. Ni (2020) finds that these statutes reduce discretionary accruals, implying that firms in such environments are more transparent. Therefore, we expect that portfolio companies operating in stakeholder-oriented states benefit from these statutes, mitigating the adverse effects of natural disasters on VC investments. To test this, we follow prior studies and collect information on the enactment of constituency statutes in each US state (Flammer and Kacperczyk 2016; Koskinen, Lu, and Nguyen 2024). The differing adoption years of these statutes allow us to implement a DiD analysis. We include an indicator variable, *Constituency statutes*, which equals 1 for the years after the enactment of these statutes in a state, and 0 otherwise. Table 13 presents the results.

The interaction between disaster damage ratio and the enactment of constituency statues are positive and significant at the 1% level in the two quarters following a natural disaster. The coefficients for disaster damage ratios remain negative and significant, confirming our baseline results. These findings suggest that while natural disasters cause physical damage and discourage VC investment in the post-disaster period, stakeholder-oriented environments mitigate these negative effects. This supports the idea that companies in stakeholder-oriented states focus on long-term sustainability, innovation, and risk mitigation, thereby reducing the negative impacts of natural disasters.

4.7 | COVID-19, Natural Disasters and VC Financing Decisions

The COVID-19 pandemic, which began in 2020, introduced significant economic challenges. Like natural disasters, the pandemic created uncertainty in financial markets. Research has investigated the stock market's reaction to pandemics, particularly COVID-19 (Javadi and Masum 2021; Ding et al. 2021; Hoang, Nguyen, and Nguyen 2022). For example, Javadi and Masum (2021) document that rising COVID-19 cases and deaths negatively affect stock returns in China. Other research emphasizes the operational challenges imposed by pandemics (Ashraf, Michas, and Russomanno 2020; Ivanov 2020; Paul and Chowdhury 2021). Ivanov (2020), for instance, finds that pandemics severely disrupt global supply chains, exacerbating operational difficulties for corporations. Startups, with fewer assets and resources, are especially vulnerable to these disruptions. Consequently, startups that have already experienced natural disasters are likely to face compounded challenges due to COVID-19, which could further affect VC investment decisions. To test this, we extend our data set to 2023 and include interaction terms between COVID-19 and natural disaster damage ratios in the analysis. *COVID-19* is a time dummy variable that equals 1 for the years 2020–2022, and 0 otherwise. Table 14 presents the results.

As expected, the coefficients of all the interaction terms between *COVID-19* and damage ratios within the four quarters following disasters are negative and highly significant at the 1%

TABLE 13 | Natural disasters, Constituency statutes, and VC investment decisions.

	Financing amount (1)	VC syndicate (2)	Avg. Financing amount (3)
Damage ratio	−0.210	−0.008	−0.401
	(0.689)	(0.984)	(0.123)
L. Damage ratio	−0.241***	−0.121***	−0.176***
	(0.000)	(0.000)	(0.000)
L2. Damage ratio	−0.181***	−0.980***	−0.125***
	(0.000)	(0.000)	(0.000)
L3. Damage ratio	−0.155	−0.262	−0.192
	(0.798)	(0.438)	(0.967)
Damage ratio* Constituency statutes	0.059	0.058	0.025
	(0.281)	(0.275)	(0.176)
L. Damage ratio* Constituency statutes	0.254***	0.126***	0.186***
	(0.000)	(0.000)	(0.000)
L2. Damage ratio* Constituency statutes	0.178***	0.100***	0.123***
	(0.000)	(0.000)	(0.000)
L3. Damage ratio* Constituency statutes	0.021	0.396	0.456
	(0.721)	(0.265)	(0.923)
Constituency statutes	−0.014	−0.005	−0.014
	(0.300)	(0.600)	(0.180)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	323,885	323,885	323,885
adj. R-sq	0.029	0.035	0.025

Note: This table reports the results for the impact of the enactment of constituency statues on the link between natural disasters and VC investment decisions. The dependent variables are various proxies for $VC_{investment}$ of firm j in quarter t: *Financing amount*, VC syndicate, and *Avg. Financing amount*. *Financing amount* is the natural logarithm of 1 plus the total amount of VC investments (in $millions) received by firm j at quarter t. *VC syndicate* is the natural logarithm of 1 plus the number of investors in a VC syndicate in firm j at quarter t. *Avg. Financing amount* is the natural logarithm of 1 plus the average VC investment amount per VC investor in firm j at quarter t. The explanatory variables are interaction terms between Constituency statutes and *Damage ratio*$_{it}$, where Constituency statutes takes the value of 1 for the years after the enactment of constituency statues in a state, and 0 otherwise; *Damage ratio*$_{it}$ is the total damage of all natural disasters in state i during quarter t divided by the annual state GDP in year t−1, and the lagged (three quarters) damage ratios. All variables are defined in Appendix B. All firm-characteristic variables are as of the end of the prior year. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with p-values in parentheses below. p-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

level. This indicates that COVID-19 exacerbated the negative impact of natural disasters, leading VCs to further reduce their investments during the pandemic. These findings align with Cumming et al. (2021), who report that VCs reduced investment amounts at the onset of COVID-19, and suggest that the combined effect of COVID-19 and natural disasters further impedes VC financing decisions.

4.8 | Green VC

Prior studies have also documented the beneficial effects of natural disasters on innovation. For instance, Miao and Popp (2014) explore the relationship between natural disasters and innovation, finding that disasters positively influence disaster-related patent activities (i.e., innovations aimed at mitigating disaster risks). They argue that natural disasters serve as the 'mother of disaster-related innovation' by prompting individuals and organizations to learn from these experiences and focus on technological innovations that aid in climate adaptation. Specifically, they contend that disasters can catalyze the invention of technologies designed to alleviate future disaster risks, such as innovations in earthquake detection and drought resistance.

VC are well known for their expertise in fostering innovation within their portfolio companies (Chemmanur and Fulghieri 2014; Chemmanur, Loutskina, and Tian 2014; Bernstein, Giroud, and Townsend 2016). Based on this, we conjecture that although natural disasters may initially reduce investments by VCs in companies located in disaster-affected areas, environmentally responsible VC firms could leverage their expertise to nurture green innovation in these companies, thereby mitigating future disaster risks. Indeed, prior research has found a positive relationship between green VC sponsorship and green innovation among portfolio firms (Hegeman and

TABLE 14 | Natural disasters, COVID-19, and VC investment decisions.

	Financing amount (1)	VC syndicate (2)	Avg. Financing amount (3)
Damage ratio	−0.239	−0.101	−0.103**
	(0.147)	(0.356)	(0.020)
L. Damage ratio	−1.103**	−0.532	−0.768***
	(0.033)	(0.311)	(0.010)
L2. Damage ratio	−0.985**	−0.419**	−0.616***
	(0.041)	(0.045)	(0.000)
L3. Damage ratio	−0.729**	−0.394	−0.523
	(0.050)	(0.174)	(0.355)
COVID-19* Damage ratio	−0.248***	−0.015***	−0.011***
	(0.000)	(0.000)	(0.000)
COVID-19* L1. Damage ratio	−0.215***	−0.013***	−0.010***
	(0.000)	(0.000)	(0.000)
COVID-19* L2. Damage ratio	−0.211***	−0.013***	−0.010***
	(0.000)	(0.000)	(0.000)
COVID-19* L3. Damage ratio	−0.219**	−0.013***	−0.010***
	(0.010)	(0.000)	(0.000)
COVID-19	−0.009	−0.006	−0.051***
	(0.235)	(0.291)	(0.000)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	383,666	383,666	383,666
adj. R-sq	0.024	0.029	0.021

Note: This table reports the results for the impact of COVID-19 on the relationship between natural disasters and VC investment decisions. The dependent variables are various proxies for $VC_{investment}$ of firm j in quarter t: *Financing amount*, *VC syndicate*, and *Avg. Financing amount*. *Financing amount* is the natural logarithm of 1 plus the total amount of VC investments (in $millions) received by firm j at quarter t. *VC syndicate* is the natural logarithm of 1 plus the number of investors in a VC syndicate in firm j at quarter t. *Avg. Financing amount* is the natural logarithm of 1 plus the average VC investment amount per VC investor in firm j at quarter t. The explanatory variables are interaction terms between COVID-19 and *Damage ratio*$_{it}$, where COVID-19 takes value of 1 for the years of 2020–2022, and 0 otherwise; *Damage ratio*$_{it}$ is the total damage of all natural disasters in state i during quarter t divided by the annual state GDP in year t−1, and the lagged (three quarters) damage ratios. All variables are defined in Appendix B. All firm-characteristic variables are as of the end of the prior year. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with p-values in parentheses below. p-values are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

Sørheim 2021; Bianchini and Croce 2022; Lin 2022; Dhayal et al. 2023). If our conjecture holds, we should observe an increase in investments by green VCs in portfolio companies located in disaster zones, aimed at fostering green technological innovations that reduce the impacts of future disasters.

To empirically test our conjecture, we follow Alakent, Goktan and Khoury (2020) and collect data on environmentally responsible VCs from SDC's VentureXpert database. We define green VCs as those firms that prioritize environmentally responsible investments. Specifically, we construct an indicator variable that takes the value of 1 if a private firm receives funding from at least one green VC, and 0 otherwise. We apply a probit model for this analysis. Table 15 presents the results.

In Column (1), the coefficient on Damage ratio is positive and statistically significant at the 10% level, suggesting that portfolio companies located in disaster-affected areas are more likely to receive funding from green VCs compared to those in non-disaster zones. Additionally, Cumming, Henriques and Sadorsky (2016) examine the determinants on cleantech VC investment. They find that oil prices significantly influence the number of cleantech VC deals, surpassing the impact of other economic, legal and institutional factors. Inspired by their study, we collect the daily West Texas Intermediate (WTI) crude oil price from *Federal Reserve Bank of St. Louis* and use the average quarterly values in our sample. In Column (2), we find that the coefficient on *WTI price* is positive and significant at the 5% level, confirming the finding reported by Cumming, Henriques and Sadorsky (2016). Particularly, our variable of interest, namely, *Damage ratio*, displays a more significant coefficient after controlling for *WTI price*, which is significant at 5%. Overall, these results indicate that natural disasters can catalyze investments from green VCs in entrepreneurial firms located in disaster-affected areas, with a focus on environmental protection and climate risk mitigation.

TABLE 15 | Natural disasters and investment decisions of green VC.

	Green VC (1)	Green VC (2)
Damage ratio	3.420*	3.533**
	(0.056)	(0.046)
L. Damage ratio	0.942	0.994
	(0.621)	(0.521)
L2. Damage ratio	0.023	0.089
	(0.991)	(0.491)
L3. Damage ratio	−4.868	−4.112
	(0.267)	(0.359)
WTI price		0.001**
		(0.043)
Controls	Yes	Yes
Year-Quarter FE	Yes	Yes
State FE	Yes	Yes
Industry FE	Yes	Yes
Obs.	323,885	323,885
Adj. R-sq	0.046	0.054

Note: This table reports the impact of natural disasters on the investment decisions amidst green venture capitalists using probit regression analysis. The dependent variable is *Green VC* of firm j in quarter t, which is an indicator variable that equals 1 if a startup receives funding from at least one green-oriented VC, and 0 otherwise. The explanatory variables are *Damage ratio*$_{it}$ and the lagged (three quarters) damage ratios. Year-Quarter, Industry, and State fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using heteroscedasticity robust standard errors. *, ** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.

5 | Conclusion

In conclusion, this study explores the under-researched area of how natural disasters influence VC investment decisions. Despite the critical role VCs play in fostering economic development through financial and managerial support to entrepreneurial ventures, their investment behaviors in the face of natural disasters have not been thoroughly examined.

In this study, we argue that natural disasters significantly disrupt company operations by damaging tangible assets, increasing financing needs, and exacerbating information asymmetry. These disruptions lead VCs to adopt more conservative investment strategies. Our empirical analysis shows a substantial reduction in VC investments in terms of financing amount and their participation in portfolio companies in disaster-affected areas. The results remain robust when examining the influence of each specific type of the natural disasters on VC financing decisions. In addition, natural disasters negatively affect VC exit strategies, particularly reducing the likelihood and increasing the time to successful exits via IPOs. Further analysis suggests that natural disasters also enhance the cost of debt financing for VC-sponsored startups, further discouraging the VC investment in disaster-affected startups. We also find that the detrimental effect of natural disasters on VC financing is less pronouncing amidst startups in stakeholder-oriented states than those in shareholder-oriented states, suggesting the benefits of long-term sustainability and risk mitigation by catering stakeholders' interests. However, an interesting finding is that environmentally responsible VCs (green VCs) are more likely to invest in disaster-affected areas, highlighting a potential avenue for resilience through green technological innovation.

Overall, the escalating frequency and severity of natural disasters necessitate a more resilient approach to VC investments, with a growing emphasis on sustainability and disaster mitigation. Our research contributes to the literature by bridging the gap in understanding the intersection of climate risk and VC, providing valuable insights for policymakers and investors in shaping future VC strategies amidst increasing climate uncertainties.

Acknowledgments

We are grateful to Denis Schweizer, Thomas Walker and Dimitrios Gounopoulos for their helpful comments and suggestions. We would also like to thank seminar participants from the University of Bath, Queen Mary University of London and Concordia University. The authors received no specific funding for this work.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings will be available in Thomson One (now is Refinitiv Eikon), and Wharton Research Data Services (WRDS) Database following an embargo from the date of publication to allow for commercialization of research findings. Data subject to third-party restrictions. The data that support the findings of this study are available from Refinitiv.com and https://wrds-www.wharton.upenn.edu/ with the permission. Restrictions apply to the availability of these data, which were used under license for this study.

Endnotes

[1] US News and World Report (2021, May 4). These Are America's Most Disaster-Prone States. Available at: www.usnews.com/news/best-states/slideshows/the-most-disaster-prone-states-in-the-us?slide=9

[2] FM Global (2020). 2020 CEO/CFO Global Risk Survey.

[3] We also use the term 'startup' in the paper.

[4] Hill (2023, March 15). Here are the most and least disaster-prone states. Available at: thehill. com/homenews/state-watch/3900281-most-least-disaster-prone-states-us

[5] The Washington Post (2023, August 29). As cost of climate disasters grows, some profit with catastrophe bonds. Available at: www.washingtonpost.com/business/2023/08/29/natural-disaster-investors-catastrophe-bonds

[6] Lifeboat Ventures (2024). Investing in Resilience: How Venture Capital Can Drive Disaster Mitigation. Available at: www.lifeboat.ventures/investing-in-resilience-how-venture-capital-can-drive-disaster-mitigation

[7] Standardized Precipitation Index is a widely used index to characterize meteorological drought on a range of timescales. In this study, we use quarterly SPI for quantifying and reporting meteorological drought. A higher index value refers to lower probability of experiencing drought.

[8]In unreported tests, we also review the correlation coefficients between the damage ratio in quarter t and the lagged damage ratios (in quarters $t-1$ to $t-3$), as well as the correlation coefficients between the lagged damage ratios themselves. The results suggest that including all these variables in the regression analysis simultaneously will not lead to a multicollinearity problem.

[9]In unreported test, we also proxy the hazard event including the VC exits through trade sales, the results remain qualitatively similar as those reported in Table 7.

[10]Fama French 5 industry classification are available at: mba. tuck. dartmouth. edu/pages/faculty/ken. french/Data_Library/det_5_ind_port. html

[11]For brevity, we only report empirical results using *Financing amount* as the dependent variable. We find similar results for *VC syndicate* and *Avg. Financing amount*. The results are available upon request.

[12]For brevity, we only report empirical results using *Financing amount* as the dependent variable. We find similar results for *VC syndicate* and *Avg. Financing amount*. The results are available upon request.

[13]The US Geological Survey (USGS) and the Federal Emergency Management Agency (FEMA) estimate that earthquakes cost the US around $14.7 billion per year. The damages caused by earthquakes were almost doubled in the past 5 years.

References

Adams, R. B., and D. Ferreira. 2007. "A Theory of Friendly Boards." *The Journal of Finance* 62, no. 1: 217–250.

Akter, M., D. Cumming, and S. Ji. 2023. "Natural Disasters and Market Manipulation." *Journal of Banking & Finance* 153: 106883.

Alakent, E., M. S. Goktan, and T. A. Khoury. 2020. "Is Venture Capital Socially Responsible? Exploring the Imprinting Effect of VC Funding on CSR Practices." *Journal of Business Venturing* 35, no. 3: 106005.

Alok, S., N. Kumar, and R. Wermers. 2020. "Do Fund Managers Misestimate Climatic Disaster Risk." *The Review of Financial Studies* 33, no. 3: 1146–1183.

Andersen, P. K., and R. D. Gill. 1982. "Cox's Regression Model for Counting Processes: A Large Sample Study." *The Annals of Statistics* 10: 1100–1120.

Andrieu, G., and A. P. Groh. 2018. "Specialist Versus Generalist Investors: Trading Off Support Quality, Investment Horizon and Control Rights." *European Economic Review* 101: 459–478.

Ashraf, M., P. N. Michas, and D. Russomanno. 2020. "The Impact of Audit Committee Information Technology Expertise on the Reliability and Timeliness of Financial Reporting." *The Accounting Review* 95, no. 5: 23–56.

Baltas, K., F. Fiordelisi, and D. S. Mare. 2022. "Alternative Finance after Natural Disasters." *British Journal of Management* 33, no. 1: 117–137.

Barber, B. M., A. Morse, and A. Yasuda. 2021. "Impact Investing." *Journal of Financial Economics* 139, no. 1: 162–185.

Barrot, J.-N., and J. Sauvagnat. 2016. "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks." *The Quarterly Journal of Economics* 131, no. 3: 1543–1592.

Bernile, G., V. Bhagwat, and P. R. Rau. 2017. "What Doesn't Kill You Will Only Make You More Risk-Loving: Early-Life Disasters and CEO Behavior." *The Journal of Finance* 72, no. 1: 167–206.

Bernstein, S., X. Giroud, and R. R. Townsend. 2016. "The Impact of Venture Capital Monitoring." *The Journal of Finance* 71, no. 4: 1591–1622.

Bertoni, F., and A. P. Groh. 2014. "Cross-Border Investments and Venture Capital Exits in Europe." *Corporate Governance: An International Review* 22: 84–99.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. "How Much Should We Trust Differences-In-Differences Estimates?" *The Quarterly Journal of Economics* 119, no. 1: 249–275.

de Bettignies, J.-E., and J. A. Brander. 2007. "Financing Entrepreneurship: Bank Finance Versus Venture Capital." *Journal of Business Venturing* 22: 808–832.

Bianchini, R., and A. Croce. 2022. "The Role of Environmental Policies in Promoting Venture Capital Investments in Cleantech Companies." *Review of Corporate Finance* 2, no. 3: 587–616.

Black, B. S., and R. J. Gilson. 1998. "Venture Capital and the Structure of Capital Markets: Banks Versus Stock Markets." *Journal of Financial Economics* 47, no. 3: 243–277.

Chaney, T., D. Sraer, and D. Thesmar. 2012. "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment." *American Economic Review* 102, no. 6: 2381–2409.

Chemmanur, T. J., and P. Fulghieri. 2014. "Entrepreneurial Finance and Innovation: An Introduction and Agenda for Future Research." *Review of Financial Studies* 27, no. 1: 1–19.

Chemmanur, T. J., E. Loutskina, and X. Tian. 2014. "Corporate Venture Capital, Value Creation, and Innovation." *Review of Financial Studies* 27, no. 8: 2434–2473.

Chemmanur, T. J., A. Signori, and S. Vismara. 2023. "The Exit Choices of European Private Firms: A Dynamic Empirical Analysis." *Journal of Financial Markets* 65: 100821.

Chen, Y.-E., C. Li, C.-P. Chang, and M. Zheng. 2021. "Identifying the Influence of Natural Disasters on Technological Innovation." *Economic Analysis and Policy* 70: 22–36.

Chircop, J., S. Johan, and M. Tarsalewska. 2020. "Does Religiosity Influence Venture Capital Investment Decisions?" *Journal of Corporate Finance* 62: 101589.

Collier, B. L., L. S. Powell, M. A. Ragin, and X. You. 2024. "Financing Negative Shocks: Evidence From Hurricane Harvey." *Journal of Financial and Quantitative Analysis*: 1–31.

Colombo, M. G., D. D'Adda, and A. Quas. 2019. "The Geography of Venture Capital and Entrepreneurial Ventures' Demand for External Equity." *Research Policy* 48, no. 5: 1150–1170.

Conti, A., N. Dass, F. Di Lorenzo, and S. J. H. Graham. 2019. "Venture Capital Investment Strategies Under Financing Constraints: Evidence From the 2008 Financial Crisis." *Research Policy* 48, no. 3: 799–812.

Crowards, T. 2000. "Comparative Vulnerability to Natural Disasters in the Caribbean." Caribbean Development Bank Staff Working Paper 1.

Cumming, D. 2008. "Contracts and Exits in Venture Capital Finance." *Review of Financial Studies* 21, no. 5: 1947–1982.

Cumming, D., and N. Dai. 2011. "Fund Size, Limited Attention and Valuation of Venture Capital Backed Firms." *Journal of Empirical Finance* 18, no. 1: 2–15.

Cumming, D., I. Henriques, and P. Sadorsky. 2016. "Cleantech' Venture Capital Around the World." *International Review of Financial Analysis* 44: 86–97.

Cumming, D., and S. A. Johan. 2008. "Preplanned Exit Strategies in Venture Capital." *European Economic Review* 52: 1209–1241.

Cumming, D. J., A. Martinez-Salgueiro, R. S. Reardon, and A. Sewaid. 2021. "COVID-19 Bust, Policy Response, and Rebound: Equity Crowdfunding and P2P Versus Banks." *The Journal of Technology Transfer* 47: 1825–1846.

David, C. R. 1972. "Regression Models and Life Tables (With Discussion)." *Journal of the Royal Statistical Society* 34: 187–220.

Dessaint, O., and A. Matray. 2017. "Do Managers Overreact to Salient Risks? Evidence From Hurricane Strikes." *Journal of Financial Economics* 126, no. 1: 97–121.

Dhayal, K. S., A. K. Giri, L. Esposito, and S. Agrawal. 2023. "Mapping the Significance of Green Venture Capital for Sustainable Development: A Systematic Review and Future Research Agenda." *Journal of Cleaner Production* 396: 136489.

Ding, W., R. Levine, C. Lin, and W. Xie. 2021. "Corporate Immunity to the COVID-19 Pandemic." *Journal of Financial Economics* 141, no. 2: 802–830.

Do, Q. A., V. Phan, and D. T. Nguyen. 2023. "How Do Local Banks Respond to Natural Disasters?" *The European Journal of Finance* 29, no. 7: 754–779.

Ewens, M., and M. Rhodes-kropf. 2015. "Is a VC partnership Greater Than the Sum of Its Parts?" *The Journal of Finance* 70: 1081–1113.

Félix, E. G. S., C. P. Pires, and M. A. Gulamhussen. 2013. "The Determinants of Venture Capital in Europe—Evidence Across Countries." *Journal of Financial Services Research* 44: 259–279.

Fiordelisi, F., G. Galloppo, and V. Paimanova. 2023. "Climate Change Fears: Natural Disasters and Investor Behaviour." *Review of Corporate Finance* 4, no. 1–2: 17–45.

Flammer, C. 2021. "Corporate Green Bonds." *Journal of Financial Economics* 142, no. 2: 499–516.

Flammer, C., and A. Kacperczyk. 2016. "The Impact of Stakeholder Orientation on Innovation: Evidence From a Natural Experiment." *Management Science* 62, no. 7: 1982–2001.

Fried, V. H., and R. D. Hisrich. 1988. "Venture Capital Research: Past, Present and Future." *Entrepreneurship Theory and Practice* 13, no. 1: 15–28.

Gan, J. 2007. "Collateral, Debt Capacity, and Corporate Investment: Evidence From a Natural Experiment." *Journal of Financial Economics* 85, no. 3: 709–734.

Gao, H., K. Li, and Y. Ma. 2021. "Stakeholder Orientation and the Cost of Debt: Evidence From State-Level Adoption of Constituency Statutes." *Journal of Financial and Quantitative Analysis* 56, no. 6: 1908–1944.

Geczy, C., J. S. Jeffers, D. K. Musto, and A. M. Tucker. 2021. "Contracts With (Social) Benefits: The Implementation of Impact Investing." *Journal of Financial Economics* 142, no. 2: 697–718.

El Ghoul, S., O. Guedhami, H. Kuang, and Y. Zheng. 2023. "Does Climate Change Exposure Matter to Stakeholders? Evidence From the Costs of High Leverage." Evidence From the Costs of High Leverage (June 30, 2023). Review of Corporate Finance, Forthcoming.

Gompers, P. A. 1995. "Optimal Investment, Monitoring, and the Staging of Venture Capital." *The Journal of Finance* 50, no. 5: 1461–1489.

Hain, D., S. Johan, and D. Wang. 2016. "Determinants of Cross-Border Venture Capital Investments in Emerging and Developed Economies: The Effects of Relational and Institutional Trust." *Journal of Business Ethics* 138: 743–764.

Hegeman, P. D., and R. Sørheim. 2021. "Why Do They Do It? Corporate Venture Capital Investments in Cleantech Startups." *Journal of Cleaner Production* 294: 126315.

Hellmann, T., and M. Puri. 2000. "The Interaction Between Product Market and Financing Strategy: The Role of Venture Capital." *Review of Financial Studies* 13: 959–984.

Heo, Y. 2022. "Climate Change, Bank Fragility, and Systemic Risk," Bank Fragility, and Systemic Risk (December 10, 2022).

Hoang, H. V., C. Nguyen, and D. K. Nguyen. 2022. "Corporate Immunity, National Culture and Stock Returns: Startups Amid the COVID-19 Pandemic." *International Review of Financial Analysis* 79: 101975.

Hoenen, S., C. Kolympiris, W. Schoenmakers, and N. Kalaitzandonakes. 2014. "The Diminishing Signaling Value of Patents Between Early Rounds of Venture Capital Financing." *Research Policy* 43, no. 6: 956–989.

Hsu, D., and R. Ziedonis. 2011. "Strategic Factor Markets and the Financing of Technology Startups: When do Patents Matter More as Signaling Devices?" Working paper.

Hsu, P.-H., H.-H. Lee, S.-C. Peng, and L. Yi. 2018. "Natural Disasters, Technology Diversity, and Operating Performance." *The Review of Economics and Statistics* 100, no. 4: 619–630.

Humphery-Jenner, M., and J.-A. Suchard. 2013. "Foreign VCs and Venture Success: Evidence From China." *Journal of Corporate Finance* 21: 16–35.

Iliev, P., and M. Lowry. 2020. "Venturing Beyond the IPO: Financing of Newly Public Firms By Venture Capitalists." *The Journal of Finance* 75, no. 3: 1527–1577.

Ivanov, D. 2020. "Predicting the Impacts of Epidemic Outbreaks on Global Supply Chains: A Simulation-Based Analysis on the Coronavirus Outbreak (COVID-19/SARS-CoV-2) Case." *Transportation Research Part E: Logistics and Transportation Review* 136: 101922.

Javadi, S., and A.-A. Masum. 2021. "The Impact of Climate Change on the Cost of Bank Loans." *Journal of Corporate Finance* 69: 102019.

Jeng, L. A., and P. C. Wells. 2000. "The Determinants of Venture Capital Funding: Evidence Across Countries." *Journal of Corporate Finance* 6: 241–289.

Kaplan, S. N., and P. Strömberg. 2004. "Characteristics, Contracts, and Actions: Evidence From Venture Capitalist Analyses." *The Journal of Finance* 59, no. 5: 2177–2210.

Klomp, J., and K. Valckx. 2014. "Natural Disasters and Economic Growth: A Meta-Analysis." *Global Environmental Change* 26: 183–195.

Koskinen, Y., H. Lu, and N. Nguyen. 2024. "Stakeholder Orientation, Environmental Performance and Financial Benefits." *Review of Corporate Finance* 4, no. 1–2: 89–125.

Krueger, P., Z. Sautner, and L. T. Starks. 2020. "The Importance of Climate Risks for Institutional Investors." *The Review of Financial Studies* 33, no. 3: 1067–1111.

Lin, L. 2022. "Venture Capital in the Rise of Sustainable Investment." *European Business Organization Law Review* 23, no. 1: 187–216.

Lockett, A., and M. Wright. 2001. "The Syndication of Venture Capital Investments." *Omega* 29, no. 5: 375–390.

Mansouri, S., and P. P. Momtaz. 2022. "Financing Sustainable Entrepreneurship: ESG Measurement, Valuation, and Performance." *Journal of Business Venturing* 37, no. 6: 106258.

Miao, Q., and D. Popp. 2014. "Necessity as the Mother of Invention: Innovative Responses to Natural Disasters." *Journal of Environmental Economics and Management* 68, no. 2: 280–295.

Moore, C. 2023. Global Venture Capital Annual Investment Shatters Records Following Another Healthy Quarter. KPMG 2022 [cited 18/09/2023]. Available From https://kpmg.com/xx/en/home/media/press-releases/2022/01/global-venture-capital-annual-investment-shatters-records-following-another-healthy-quarter.html.

Nahata, R., S. Hazarika, and K. Tandon. 2014. "Success in Global Venture Capital Investing: Do institutional and Cultural Differences Matter?" *Journal of Financial and Quantitative Analysis* 49, no. 4: 1039–1070.

National Venture Capital Association. 2023. *National Venture Capital Association 2023 Yearbook*. Virginia: National Venture Capital Association.

Ni, X. 2020. "Does Stakeholder Orientation Matter for Earnings Management: Evidence From Non-Shareholder Constituency Statutes." *Journal of Corporate Finance* 62: 101606.

Ni, X., W. Song, and J. Yao. 2020. "Stakeholder Orientation and Corporate Payout Policy: Insights From State Legal Shocks." *Journal of Banking & Finance* 121: 105970.

Ning, Y., W. Wang, and B. Yu. 2015. "The Driving Forces of Venture Capital Investments." *Small Business Economics* 44: 315–344.

Oh, C. H., and J. Oetzel. 2011. "Multinationals' Response to Major Disasters: How Does Subsidiary Investment Vary in Response to the Type of Disaster and the Quality of Country Governance?" *Strategic Management Journal* 32, no. 6: 658–681.

Ouazad, A., and M. E. Kahn. 2022. "Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters." *The Review of Financial Studies* 35, no. 8: 3617–3665.

Pagano, M., F. Panetta, and L. Zingales. 1998. "Why Do Companies Go Public? An Empirical Analysis." *The Journal of Finance* 53, no. 1: 27–64.

Pástor, Ľ., R. F. Stambaugh, and L. A. Taylor. 2021. "Sustainable Investing in Equilibrium." *Journal of Financial Economics* 142, no. 2: 550–571.

Paul, S. K., and P. Chowdhury. 2021. "A Production Recovery Plan in Manufacturing Supply Chains for a High-Demand Item during COVID-19." *International Journal of Physical Distribution & Logistics Management* 51, no. 2: 104–125.

Rasmussen, T. 2004. "Macroeconomic Implications of Natural Disasters in the Caribbean." Working paper.

Rehse, D., R. Riordan, N. Rottke, and J. Zietz. 2019. "The Effects of Uncertainty on Market Liquidity: Evidence From Hurricane Sandy." *Journal of Financial Economics* 134, no. 2: 318–332.

Reuer, J. J., and R. Ragozzino. 2012. "The Choice between Joint Ventures and Acquisitions: Insights From Signaling Theory." *Organization Science* 23, no. 4: 1175–1190.

Rosenbaum, P. R., and D. B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70, no. 1: 41–55.

Saunders, A., and S. Steffen. 2011. "The Costs of Being Private: Evidence From the Loan Market." *Review of Financial Studies* 24, no. 12: 4091–4122.

Schenone, C. 2010. "Lending Relationships and Information Rents: Do Banks Exploit Their Information Advantages?" *Review of Financial Studies* 23, no. 3: 1149–1199.

Shuwaikh, F., M. Hughes, S. Brinette, and S. Khemiri. 2023. "Investment Decisions Under Uncertainty: Corporate Venture Capital As a Real Option." *International Journal of Finance & Economics* 29, no. 2: 2452–2471

Tian, X., G. F. Udell, and X. Yu. 2016. "Disciplining Delegated Monitors: When Venture Capitalists Fail to Prevent Fraud by Their IPO Firms." *Journal of Accounting and Economics* 61, no. 2: 526–544.

Tian, X., Y. Wang, and K. Ye. 2023. "How Does Policy Uncertainty Affect Venture Capital?" *The Review of Corporate Finance Studies*: cfad023.

Tölö, E., and M. Virén. 2021. "How Much Do Non-Performing Loans Hinder Loan Growth in Europe?" *European Economic Review* 136: 103773.

Tversky, A., and D. Kahneman. 1974. "Judgment Under Uncertainty: Heuristics and Biases: Biases in Judgments Reveal Some Heuristics of Thinking Under Uncertainty." *Science* 185, no. 4157: 1124–1131.

Västfjäll, D., E. Peters, and P. Slovic. 2014. "The Affect Heuristic, Mortality Salience, and Risk: Domain-Specific Effects of a Natural Disaster on Risk-Benefit Perception." *Scandinavian Journal of Psychology* 55, no. 6: 527–532.

Wang, J. 2023. "Natural Disasters and Firm Leasing: A Collateral Channel." *Journal of Corporate Finance* 82: 102428.

Winton, A., and V. Yerramilli. 2008. "Entrepreneurial Finance: Banks Versus Venture Capital." *Journal of Financial Economics* 88: 51–79.

Zhao, X.-X., M. Zheng, and Q. Fu. 2022. "How Natural Disasters Affect Energy Innovation? The Perspective of Environmental Sustainability." *Energy Economics* 109: 105992.

Appendix A

TABLE A1 | Distribution of natural disasters.

Year quarter	Date	Disaster name	End month/day	Damage	Disaster type	Location (state abbreviation)
1991q3	8/16	Bob	8/29	1.5 billion	Hurricane	MA, ME, NC, NH, NY, RI
1991q4	10/19	Firestorm Oakland Hills	10/20	1.5 billion	Wildfire	CA
1992q3	8/16	Andrew	8/29	27.3 billion	Hurricane	AL, FL, LA, MS
1992q3	9/5	Iniki	9/13	3.1 billion	Typhoon	HI
1993q1	3/12	Blizzard	3/15	2 billion	Blizzard	AL, CT, FL, GA, MA, MD, NJ, OH, SC, VA, VT
1994q1	1/17	Earthquake Northridge	1/17	31 billion	Earthquake	CA
1994q2	6/30	Alberto	7/7	1 billion	Hurricane	AL, FL, GA
1995q3	9/27	Opal	10/6	4.7 billion	Hurricane	AL, FL, GA, LA, MS, NC, SC
1996q1	1/6	Blizzard	1/10	3 billion	Blizzard	CT, DE, IN, KY, MA, MD, NC, NJ, NY, PA, VA, WV
1996q3	8/23	Fran	9/10	5 billion	Hurricane	NC, SC, VA, WV
1998q1	1/4	Ice storm	1/10	6 billion	Ice storm	ME, NH, NY, VT
1998q3	8/19	Bonnie	8/30	1 billion	Hurricane	NC, VA
1998q3	9/15	Georges	10/1	9.37 billion	Hurricane	AL, FL, LA, MS
1999q3	9/7	Floyd	9/19	6.5 billion	Hurricane	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
2001q2	6/5	Allison	6/20	9 billion	Hurricane	AL, FL, GA, LA, MS, PA, TX
2003q3	9/6	Isabel	9/20	3.6 billion	Hurricane	DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV
2003q4	10/25	Southern California Wildfires	12/5	1.33 billion	Wildfire	CA
2004q3	8/9	Charley	8/15	16.9 billion	Hurricane	FL, GA, NC, SC
2004q3	9/13	Jeanne	9/29	7.94 billion	Hurricane	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
2004q3	9/2	Ivan	9/25	26.1 billion	Hurricane	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
2004q3	8/24	Frances	9/10	10.1 billion	Hurricane	DE, FL, GA, MD, NC, NJ, PA, SC, VA
2005q3	7/4	Dennis	7/18	3.98 billion	Hurricane	AL, FL, GA, MS, NC
2005q3	8/23	Katrina	8/31	125 billion	Hurricane	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
2005q3	9/18	Rita	9/26	18.5 billion	Hurricane	AL, AR, FL, LA, MS
2005q4	10/15	Wilma	10/27	27.4 billion	Hurricane	FL
2008q2	6/7	Midwest flooding	7/1	6 billion	Floods	IA, IL, IN, MN, MO, NE, WI
2008q3	8/25	Gustav	9/7	8.31 billion	Hurricane	AR, LA, MS
2008q3	9/1	Ike	9/15	38 billion	Hurricane	AR, LA, MO, TN, TX
2011q1	1/31	Groundhog Day Blizzard	2/3	1.8 billion	Blizzard	CT, IA, IL, IN, KS, MA, MO, NJ, NM, NY, OH, OK, PA, TX, WI

(Continues)

TABLE A1 | (Continued)

Year quarter	Date	Disaster name	End month/day	Damage	Disaster type	Location (state abbreviation)
2011q3	8/21	Irene	8/30	14.2 billion	Hurricane	CT, MA, MD, NC, NJ, NY, VA, VT
2011q3	9/2	Lee Tropical Storm	9/7	2.8 billion	Hurricane	AL, CT, GA, LA, MD, MS, NJ, NY, PA, TN, VA
2012q3	8/21	Isaac	9/3	3.11 billion	Hurricane	FL, LA, MS
2012q4	10/22	Sandy	11/2	68.7 billion	Hurricane	CT, DE, MA, MD, NC, NH, NJ, NY, OH, PA, RI, VA, WV
2013q2	4/18	Illinois Flooding	No accurate recording	1 billion	Floods	IL, IN, MO
2013q3	9/9	Colorado Flooding	12/31	1 billion	Floods	CO
2015q3	9/9	California Wildfire	9/19	4.8 billion	Wildfire	CA
2016q3	9/28	Matthew	10/10	16.47 billion	Hurricane	FL, GA, NC, SC
2017q3	8/17	Harvey	9/2	125 billion	Hurricane	TX, LA, AL
2017q3	8/30	Irma	9/14	77.16 billion	Hurricane	FL, SC, GA
2017q3	9/16	Maria	10/2	91.61 billion	Hurricane	FL
2017q4	10/8	California Wildfire	10/9	18 billion	Wildfire	CA
2018q3	8/31	Florence	9/18	24.23 billion	Hurricane	NC, SC
2018q4	10/7	Michael	10/16	25.5 billion	Hurricane	FL, GA
2018q4	11/8	Camp Fire	11/25	16.65 billion	Wildfire	CA
2019q3	8/24	Dorian	9/10	5.1 billion	Hurricane	FL, GA, SC, NC
2019q3	9/17	Imelda	9/19	5 billion	Hurricane	TX
2019q3	7/4	Ridgecrest	7/5	5.3 billion	Earthquake	CA

Note: Appendix A describes the 47 natural disasters that occurred in the US territory from 1990 to 2019. Names, years and locations of each natural disaster are obtained from SHELDUS database. Abbreviations for US states used in the table: AL (Alabama), AK (Alaska), AZ (Arizona), AR (Arkansas), CA (California), CO (Colorado), CT (Connecticut), DE (Delaware), FL (Florida), GA (Georgia), HI (Hawaii), ID (Idaho), IL (Illinois), IN (Indiana), IA (Iowa), KS (Kansas), KY (Kentucky), LA (Louisiana), ME (Maine), MD (Maryland), MA (Massachusetts), MI (Michigan), MN (Minnesota), MS (Mississippi), MO (Missouri), MT (Montana), NE (Nebraska), NV (Nevada), NH (New Hampshire), NJ (New Jersey), NM (New Mexico), NY (New York), NC (North Carolina), ND (North Dakota), OH (Ohio), OK (Oklahoma), OR (Oregon), PA (Pennsylvania), RI (Rhode Island), SC (South Carolina), SD (South Dakota), TN (Tennessee), TX (Texas), UT (Utah), VT (Vermont), VA (Virginia), WA (Washington), WV(West Virginia), WI (Wisconsin) and WY (Wyoming).

Appendix B

TABLE B1 | Variable definitions.

Variable	Definition	Source
Natural disaster variables		
Damage ratio	Total damage of all natural disasters in a state in a given quarter, scaled by the annual state GDP in the prior year	SHELDUS
Disaster	Dummy variable that takes on a value of 1 if a natural disaster occurred in the state in a given quarter, and 0 otherwise. A disaster is defined as a natural disaster causing more than $1 billion in losses within 31 days (Barrot and Sauvagnat 2016). For the list of corresponding disasters, please refer to Appendix A.	SHELDUS
Disaster type	The damage ratio for different types of disasters, which is the total damage of a certain type of natural disasters in state i during quarter t divided by the annual state GDP in the prior year, Disaster types include hurricanes, flood, winter storm, wildfire, and earthquake.	SHELDUS
Natural disaster risk	The overall natural disaster risk score at the county level. We match the score with portfolio company's location.	The Federal Emergency Management Agency

(Continues)

TABLE B1 | (Continued)

Variable	Definition	Source
VC variables		
Financing amount	The natural logarithm of 1 plus the aggregate amount of VC investments (in $millions) received by a portfolio company in a quarter	Thomson One
VC syndicate	The natural logarithm of 1 plus the number of VC investors in a portfolio company in a quarter	Thomson One
Avg. Financing amount	The natural logarithm of 1 plus the average investment amount (in $millions) per VC investor in a portfolio company in a quarter	Thomson One
IPO	An indicator variable that equals 1 if the exit choice is IPO, and 0 otherwise	Thomson One
All exits	An indicator variable that equals 1 if venture capitalists successfully exit from their portfolio firms via by IPO or trade sales (acquisitions), and 0 if the portfolio firms are liquidated.	Thomson One
Success IPO	The duration it takes for a VC backed private firm to go public: the days between the initial date an entrepreneurial firm receiving VC sponsorship and the IPO listing date	Thomson One
Green VC	An indicator variable that equals 1 if a startup receives funding from at least one green oriented VC, and 0 otherwise	SDC's VentureXpert
Other variables		
Tobin Q	The average value of Tobin Q at the industry level. Industry is defined according to the 3-digit SIC code. Tobin Q is measured as the book value of total assets plus the market value of common equity minus the book value of common equity, scaled by the book value of total assets	Compustat
Cashflow	The average value of cashflow at the industry level. Industry is defined according to the 3-digit SIC code. Cashflow is computed as the operating cashflow scaled by the total assets	Compustat
Sales growth	The average sales growth rate at the industry level. Industry is defined according to the 3-digit SIC code	Compustat
Age	Difference between a specific VC financing year and a start up's founding year	Thomson One
R&D	The average ratio of research and development expenditures over total assets at the industry level. Industry is defined according to the 3-digit SIC code	Compustat
Income per capita	Personal income per capita of a U.S. state	US Bureau of Economic Analysis
State GDP	Natural logarithm of the annual GDP of a U.S. state	U.S. Census Bureau
Precipitation	Average precipitation of a U.S. state in a given quarter proxied with the SPI index, which is expressed as standard deviations that the observed precipitation would deviate from the long-term mean, for a normal distribution and fitted probability distribution for the actual precipitation record	PRISM Climate Group
Temperature	Average temperature (in Fahrenheit degree) of a U.S. state in a given quarter	PRISM Climate Group
Financial stability	The net loan losses to average total loans at a state level in a given year	Federal Reserve Economic Data
Loan spreads	The interest rate spreads above LIBOR plus annualized upfront fees	Refinitiv Loan Pricing Corporation (LPC) DealScan
Constituency statutes	An indicator variable that takes the value of 1 for the years after the enactment of constituency statues in a state, and 0 otherwise	Koskinen, Lu and Nguyen (2024)
COVID-19	A time dummy that equals 1 for the years of 2020 – 2022, and 0 otherwise	Cumming et al. (2021)
WTI price	The quarterly average value of the daily West Texas Intermediate (WTI) crude oil price	Federal Reserve Bank of St. Louis