Natural Disasters and Economic Dynamism: Evidence from U.S. Entrepreneurial Activity

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Abstract

Recent events have spurred an interest in examining the economic effects of natural disasters. However, the literature has tended to focus on country-level evidence and single-item measures to investigate the role of natural disasters on measures of economic activity like entrepreneurship. In this paper, we use a variety of entrepreneurship measures in a sample of 48 states from 1998 to 2018 in the US. Building on prior studies, we find that disaster effects vary by entrepreneurship type—the rate of new entrepreneurs and start-up job creation rise in the aftermath of natural disasters while the opportunity share of new entrepreneurs and start-up survival decline. These results provide a more nuanced view of the link between natural disasters and entrepreneurship than reported in the literature. We interpret our findings in the context of economic dynamism and discuss policy implications.

Keywords

Natural Disasters, Entrepreneurship, Economic Dynamism

JEL Codes

L26, M13, Q50, Q54

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1. Introduction

A growing concern for state governments across the U.S. is the effect of natural disasters on small business activity (FEMA 2019). Given that the frequency and severity of disaster events continue to rise (Hoeppe 2016; NOAA 2020; Gunby and Coupe 2022), and that business formation remains a key driver of economic dynamism (Davis and Haltiwanger 1992; Davis et al. 1996; Haltiwanger et al. 2013), determining how natural disasters impact entrepreneurs and small businesses is critical to sound public policy.

Although the literature on the economic effects of disasters is vast, it is typically restricted to a narrow set of events with mixed results (Hochrainer 2009). For example, Dolfman et al. (2007) report that Hurricane Katrina severely damaged Orleans parish–the hardest hit parish in Louisiana–for years after the event while out-migration likely had a favorable impact on neighboring parishes. Nielsen-Pincus et al. (2013) find that the stimulatory nature of fire management efforts, rebuilding, and the inflow of public funds alleviate the adverse effect of wildfires on the western U.S. counties. Mantell et al. (2013) report that Hurricane Sandy reduced New Jersey's state income by $1 billion in 2012, while predicting recovery activity to provide $300 million of stimulus. More recently, Best and Burke (2019) found that the 2010 earthquake in Haiti has had long-term negative implications on the economy.

These studies, although insightful, disregard one of the most important drivers of economic activity: entrepreneurship and small business formation (Davis and Haltiwanger 1992; Davis et al. 1996; Haltiwanger et al. 2013; Decker et al. 2014). The few exceptions seek a causal link between natural disasters and entrepreneurship by exploring country-level business registrations (Miao and Popp 2014; Boudreaux et al. 2019; Boudreaux et al. 2021, 2022), the effect on investments by and stock prices of small- and medium-size firms (Capelle-Blancard and Laguna 2010; Oh and Oetzel

2011), disaster response by social entrepreneurs (Dutta 2017), and network resource sharing (Islam and Nguyen 2018).

The identification of a disaster effect on small business activity needs careful consideration (Miao and Popp 2014). On one hand, the disruption caused by disasters elevate the risk of closure for incumbent firms with direct damages, income loss, and infrastructure destruction stifling local activity. On the other hand, studies examining entrepreneurship trends at national and sub-national levels report that, conditional on economic development, the disruption driven by disasters tend to be short-lived and accompanied by new entrepreneurial prospects, particularly in regions that need extensive clean-up and repair (Dolfman et al. 2007; Boudreaux et al. 2019). Further, the response to disaster events depends on whether the resulting activity is opportunity- or necessity-motivated (Fairlie and Fossen 2018).

Provided the uncertainty regarding disaster effects (Ćorić and Šimić, 2021) on different forms of entrepreneurship, an issue largely omitted in the prior literature, we turn to the Kauffman Indicators that track small business activity in the U.S. states in alternate dimensions such as start-up formation, job creation, survival, and opportunity considerations. We discuss potential endogeneity in disaster costs (Miao and Popp 2014; Miao et al. 2018) and model various lag structures to capture delayed impacts that may materialize over time (Miao et al. 2018; Botzen et al. 2019).

Our main finding is that disaster effects show large heterogeneity by entrepreneurship type, which paints a more nuanced picture than suggested by previous studies (Grube and Storr 2018; Boudreaux et al. 2019). That is, it is incomplete to claim that disasters simply discourage or encourage entrepreneurship activity. Rather, disasters have heterogenous effects on entrepreneurship activity. In particular, we find that business disruptions and the uncertainty caused by disasters lower early start-up survival and force entrepreneurs to move from seeking opportunity to fulfilling necessity. By contrast, recovery activity, public aid and private insurance, and the public-to-private shift in the U.S. disaster management efforts raise start-up formation and job creation, which drive an overall improvement in state-level entrepreneurship. Hence, disasters have heterogenous effects on entrepreneurship, depending on the measure.

Our study makes several contributions to the entrepreneurship and natural disaster literatures. We extend the entrepreneurship literature by examining disaster impacts on alternative dimensions of small business activity captured by the Kaufmann Indicators. This approach improves on prior work that investigates single-item measures such as new business registrations, stock prices, social entrepreneurship, or network resource sharing. These studies overlook potentially disparate effects on start-up formation, job creation, survival, and opportunity activity, key pieces in understanding the nuanced ways in which disaster events impact small businesses. Consider Boudreaux et al. (2019), for example, who find an overall negative link between natural disasters and business registrations, which likely masks heterogeneous effects on incumbent firms and new entrants.

We also extend the natural disasters literature by studying disaster effects on entrepreneurs across the U.S. states, the first state-level study on the subject, unlike previous work that examines country-level data, a high level of aggregation that may overlook important regional heterogeneity. We consider states the proper unit of analysis because disaster impacts are felt statewide (Dolfman et al. 2007; Nielsen-Pincus et al. 2013), increasingly alarming state officials (FEMA 2019), while the recovery process is mostly handled by states including public funds routed to state governments first. This approach has the added benefit of lessening heterogeneous development and institutional quality issues that confound country-level estimates (Hochrainer 2009; Klomp and Valckx 2014; Botzen et al. 2019).

The study is organized as follows. The second section describes our dataset and empirical methods we use to measure disaster effects on entrepreneurial activity. The third section presents estimation results, while the fourth section offers discussion in the context of economic dynamism and policy implications. We conclude in the fifth section with a summary of findings and ideas for future work.

2. Estimation

The section begins with a description of our model before turning to data and concerns pertaining to endogeneity.

2.1. Model

We regress an entrepreneurship metric E_{it} on its first lag E_{it-1}, which accounts for dynamic effects (Dutta and Sobel 2016; Boudreaux et al. 2019), state-level control variables collected in SC_{it}, and a set of unobserved effects:

$$E_{it} = \gamma_0 + \gamma_1 E_{it-1} + \sum_{j=0}^{n} \gamma_{2j} D_{it-j} + \gamma_3 SC_{it} + \eta_i + \tau_t + u_{it} \quad (1)$$

where D_{it} is the disaster damage measured in the U.S. dollars to crops and farmland in addition to public and private property including infrastructure and facilities.

It is essential to consider intertemporal dynamics, since natural disasters may have a lagged impact on entrepreneurship activity with the aggregate impact accumulating for several years after disasters occur (Miao et al. 2018; Botzen et al. 2019). To capture the implied long-term effect, we introduce dynamic models that increase the number of lags gradually from zero to five: $n = 0 \ldots 5$. In this setting, the sum of estimated coefficients on contemporaneous value and all lags ($\sum_{j=0}^{n} \gamma_{2j}$) determines the average impact of disaster damages on small business activity.

We rely on standard controls from the entrepreneurship literature in populating vector SC_{it} (Holtz-Eakin et al. 1994; Blanchflower and Oswald 1998; Bruce and Deskins 2012; Boudreaux and Nikolaev 2019; Giebel and Kraft 2019). For example, we account for states' business climate by including the number of establishments, number of firms, and total employment. Provided that entrepreneurs often face credit constraints, we measure credit access by the number of commercial banks, their assets, deposits, equity, and net income. We control for demographic trends by adding state population, prime-age population (aged from 18 to 65) more likely to be entrepreneurial, and state income, which tracks the aggregate value of all salaries, wages, and tips.

Entrepreneurial activity may depend on state-level factors that are difficult to quantify in a standardized manner: geographic location, economic structure, etc. We include state-specific fixed effects in η_i to capture relevant information such as geographic and structural advantages. We also include year fixed effects in τ_t to account for aggregate shocks affecting all states over time.

2.2. Data

The sample is a panel of annual observations for 48 contiguous states in the U.S. (sans Alaska and Hawaii) for the period from 1998 to 2018.

To document potentially disparate impacts, thus extend the relevant literature, we examine several dimensions of entrepreneurship as summarized by the Kauffman Indicators.[1] In particular, we use the rate of new entrepreneurs (percent of population that starts a new business), opportunity share (percent of entrepreneurs that start a business by choice), start-up early job creation (number of jobs created by startups during their first year), start-up early survival (percent of startups active after one year), and a summary index that averages these four metrics to assess the overall level of

[1] Detailed data on the Kauffman Indicators of entrepreneurship are available at https://indicators.kauffman.org.

entrepreneurial activity in the state. Table 1 reports state-level data for all indicators and Figure 1 provides a map of spatial variation in the summary index.

The disaster variable D_{it} tracks damages to crops and property incurred during emergencies and major disasters, which are collected from the Arizona State University's Spatial Hazard Events and Losses Data for the United States database and summarized by Table 2. Importantly, damages tend to be higher in populous and wealthy states, as shown in Figure 2, due to the greater monetary value of land and property. We account for economic size, following Noy and Nualsri (2011) and Miao et al. (2018), by scaling disaster damages by state population and state income in alternative specifications.

The control vector contains information on states' business climate (establishments, firms, and employment) that are collected from the Census County Business Patterns and credit access (commercial banks, bank assets, deposits, equity, and net income) from the FDIC historical tables. Data on demographic factors (population, prime-age population, and income) are from the Census Community Survey. Table 3 presents summary statistics for these control variables in addition to entrepreneurship and disaster measures.

Disaster damages and several controls are measured in the U.S. dollars. We adjust these by 2015 dollars to take account of inflation. All variables are logged for ease of interpretation, adding one to treat zero observations, except damages that are scaled by state population or income.

2.3. Endogeneity

Some analysts classify natural disasters as exogenous (Kosmopoulou and Zhou 2014), while others examine potential endogeneity in damages (Miao and Popp 2014; Miao et al. 2018). This is driven by the insight that states that experience destructive events and economic adversity as a result are likely to invest in mitigation, infrastructure construction in particular, which may affect resilience and thus monetary damages in future events.

To determine whether disaster damages need to be considered endogenous in our sample, we use the augmented Durbin-Wu-Hausman (DWH) test from Davidson and MacKinnon (1993). The test follows the control function approach of collecting the residuals from a first-stage model that regresses potentially endogeneous damages (D) on the same controls from Equation 1 (X) and a set of exogenous instruments (Z).

$$D_{it} = \delta_0 + \delta_1 X_{it} + \delta_2 Z_{it} + \varepsilon_{it} \tag{2}$$

The predicted residuals ($\hat{\varepsilon}_{it}$) are then inserted into Equation 1 as an additional regressor that yields:

$$E_{it} = \gamma_0 + \gamma_1 E_{it-1} + \sum_{j=0}^{n} \gamma_{2j} D_{it-j} + \gamma_3 SC_{it} + \gamma_4 \hat{\varepsilon}_{it} + \eta_i + \tau_t + u_{it} \tag{3}$$

in which case a rejection of the null hypothesis $H_0: \gamma_4 = 0$ would indicate that damages are in fact endogenous (Wooldridge 2010).

We add three instruments to Equation 2 that are based on the frequency of disaster events. These are the duration of disasters with property damages (length in days of all disaster events that damaged property), duration of disasters with crop damages (same for crops), and disaster records (count of raw data records used in calculating total damages). Broadly speaking, these frequency-based instruments measure how often disasters occur and how long they last.

There are two reasons to consider these instruments. First, both frequency and severity of natural disasters have risen in recent years. Of these trends, frequency as measured by duration or records is driven by natural factors–those related to climate change in particular (Pew 2018; IPCC 2018)–that are exogenous in the entrepreneurship model.[2] On the other hand, severity as measured

[2] Duration variables measure the length of disasters in which any damage occurs to property and crops. For hurricanes, for example, duration counts the number of days during which sustained surface wind speeds exceed 74 mph (NOAA), which depends on exogenous climate patterns but not economic priors nor the ex-post state reaction to hurricanes such

by dollar damages is driven by natural factors and the social response including mitigation efforts, making damages potentially endogeneous.

Second, a valid instrument would affect entrepreneurial activity only through its impact on disaster damages, which aggregate losses to property and crops. This condition generally holds for the frequency-based variables: the longer the duration of natural disasters the larger should be the damage to property and crops; the greater the number of underlying data records the larger should be the damage to property and crops.

We apply DWH tests to two disaster measures, damages scaled by population and income, at all lags ($n = 0 \dots 5$) for five entrepreneurship metrics. Across the board, we fail to reject the null hypothesis at conventional significance levels, indicating that endogeneity in damages is at best a minor concern in our data. We therefore proceed with least squares estimates for Equation 1.

3. Results

Table 4 presents estimates for Equation 1 in which disaster severity is measured by dollar damages scaled by population. All specifications include the lagged entrepreneurship metric and the full set of controls in addition to state and year fixed effects, while clustering standard errors at state level to avoid heteroscedasticity and serial correlation.

Results for control variables, though not reported for brevity, are generally consistent with our priors. For example, states' prime-age population and income are associated with higher rates of new entrepreneurs, start-up job creation, and overall entrepreneurial activity. Similarly, controls for credit access provide useful insight; commercial bank deposits, equity capital, and net income raise job creation, opportunity activity, and survival rates.

as mitigation spending. Our focus on frequency-based factors is in line with Miao et al. (2021) who use the exogenous variation in the number of flood events states experience each year in studying losses due to flooding.

As for the variable of interest, disaster effects vary by entrepreneurship type and over time. For example, disaster damages raise the rate of new entrepreneurs and start-up early job creation, with results significant at conventional levels over lags of three to five years. The opportunity share and start-up early survival fall after disasters with the relevant effects appearing at lags one to five. The impact on the summary index of entrepreneurship is positive and significant at lag four.

Table 5 presents estimates for models in which disaster damages are scaled by state income. These results are qualitatively similar to those from Table 4, which supports the earlier finding that natural disasters lead to significant effects that vary by entrepreneurship type.

The impact of disaster events may depend on the availability of insurance payments (Lewis and Nickerson 1989). For example, those with coverage are financially protected, which alleviates the adverse impact on operations while also providing seed capital for new business opportunities. Accordingly, we extend Equation 1 using data on crop indemnity payments–losses insured by the Department of Agriculture for designated perils–for each state and year (CI_{it}) alongside interaction terms for damages and insurance ($D_{it-j} * CI_{it}$) at all lags ($j = 0 ... 5$). Tables 6 and 7 present results for models in which damages are scaled by population and income respectively. These are similar to estimates reported in Tables 4 and 5.

The lagged dependent variable E_{it-1} was included to control for dynamic effects. However, Nickell (1981) argues that least squares estimates in first-order autoregressive models with fixed effects may be biased if i (number of states) is large relative to t (number of years). To determine the empirical significance of this bias, we re-run all specifications in Tables 6 and 7 in the absence of lagged entrepreneurship. Tables 8 and 9 present these estimates, which are in line with preceding results and alleviate bias concerns.

It is worthwhile to discuss the economic significance of our findings. For this task, we turn to billion-dollar disasters, using the point estimates to predict their influence on entrepreneurship, since natural disasters have become markedly more destructive in recent years. In fact, the National Oceanic and Atmospheric Administration reports 341 weather/climate events since 1980 in which inflation-adjusted damages exceeded $1 billion with a total cost of $2.5 trillion. These events occur with regularity: 2022 is the eighth consecutive year with ten or more billion-dollar disasters; while the average for the entire period 1980-2022 is 7.9 billion-dollar events per year, that for the most recent five years (2018-2022) stands at 17.8 events.[3]

The occurrence of major events appears to cause economically meaningful entrepreneurial effects. For example, the rate of new entrepreneurs features a sample mean of 0.0029, as reported in Table 3, while the predicted mean for billion-dollar disasters is 0.0032; these events raise start-up formation by 10.4 percent from 2.9 to 3.2 residents out of 1,000 in a given year. Results for the remaining metrics are in alignment: billion-dollar events raise start-up job creation by 7.1 percent, reduce opportunity share by 1 percent, reduce start-up survival by 0.7 percent, and raise the overall level of entrepreneurial activity by 5.3 percent.

A note on the Covid-19 pandemic may be useful in context. Although not a natural disaster per se, the pandemic caused similarly diverse economic impacts: While customer-facing industries such as restaurants, hotels, and airlines experienced shutdowns, there were opportunities for others able to adapt to and capitalize on rapid technological shifts such as remote work software and food delivery (Haltiwanger 2021). Overall, the number of new business applications rose by 38 percent in the year 2021 compared to 2019 (U.S. Census Bureau 2021).

4. Discussion

[3] Data and background information on billion-dollar disasters are available at https://www.ncdc.noaa.gov/billions/.

The previous section shows evidence of heterogenous effects–disasters inhibiting rates of start-up survival and opportunity activity while promoting rates of new entrepreneurs and job creation with an overall favorable impact on small businesses. We now interpret these findings in the context of economic dynamism before turning to policy implications.

Natural disasters may discourage certain forms of entrepreneurship. For example, consider the initial disruption due to disaster events, which increases the risk of closure for incumbent firms. In particular, direct damages to property and infrastructure, economic dislocation, and income loss disrupt the local business environment, thereby stifling existing entrepreneurs (Galbraith and Stiles 2006; Kosova and Lafontaine 2010; FEMA 2019).

A related reason to expect reduced entrepreneurship is the uncertainty created by disasters. Although some entrepreneurs prosper under uncertain circumstances by tweaking business models or pivoting to capitalize on sudden changes in the marketplace, many do not consider it worthwhile and shut down instead (Navis and Ozbek 2017). In fact, it is reported that more than 40 percent of small businesses never reopen after natural disasters in the U.S. (FEMA 2019).

Meanwhile, other types of entrepreneurship may thrive in the aftermath of natural disasters. In particular, new opportunities arise–given the stimulatory nature of cleanup, repair, construction, and mitigation activity–such that incumbents that survive a disaster and new start-ups experience higher demand (Strobl 2011; Nielsen-Pincus et al. 2013). Moreover, although recovery periods are transitory, they feature infrastructure investment with lasting benefits such as sustained production and payrolls in affected areas (Mantell et al. 2013).

Another channel for a favorable effect is the mix of public assistance and private insurance. Such funding supports entrepreneurial recovery by helping incumbents to weather disaster periods while also providing liquidity to failed entrepreneurs with which they can start new firms to make up for disaster-driven closures (Lewis and Nickerson 1989; Kousky et al. 2018). In fact, the Federal Emergency Management Agency often works with the U.S. Small Business Association (SBA) to assist incumbents and new businesses in disaster regions.[4]

We also highlight the increasingly significant role the private sector has played in the U.S. disaster management efforts since the 1980s, while public agencies have transitioned into oversight (Boin and McConnell 2007). The shift represents a proliferation of opportunities, which is evident in the observation that private activity driven by disasters has grown into a major part of aggregate economic output in states susceptible to major events (McKnight and Linnenluecke 2016).

Together, business disruptions and the uncertainty caused by natural disasters reduce start-up survival and opportunity-based entrepreneurship while recovery activity, public aid and private insurance, and the shift in the U.S. disaster management policy support new start-up formation and job creation. The mixed effects on different forms of entrepreneurship highlight churn at firm level (Aloi et al. 2021), akin to creative destruction disrupting supply chains to generate space for new entrepreneurs (Schumpeter 1942), while the overall favorable impact on small businesses provides impetus for dynamism (Davis and Haltiwanger 1992; Davis et al. 1996; Haltiwanger et al. 2013).

In reporting improved entrepreneurship and dynamism, our intention is not to suggest that natural disasters are, for the lack of a better word, good for states. Aside from their monetary cost, disasters bring about considerable injury and death for which the social loss is difficult to quantify. Nonetheless, our findings present a reason for optimism in an otherwise gloomy picture insofar as they highlight human grit and ingenuity in the face of incredible difficulty.

With that in mind, we caution policymakers and entrepreneurs against the presumption that natural disasters are uniformly harmful, urging them to recognize that recoveries are a joint process

[4] Detailed guidelines for post-disaster loans and grants to individuals and small businesses are available from SBA at https://www.sba.gov/category/keywords/fema.

financed primarily by the public sector and carried out by private entities. Therefore, we advocate policies to streamline the delivery of relief funds and raise mitigation spending, while encouraging entrepreneurs to invest in insurance and resilience, all of which will support small business activity (Boudreaux et al. 2021). Such a boost would be particularly welcome in the face of recent declines in dynamism (Hathaway and Litan 2014; Fed 2017) with data showing that roughly half of all U.S. firms fail in the first five years (National Business Capital and Services 2019).

5. Conclusion

Among the many questions surrounding climate change, measuring the economic effects of natural disasters is of paramount concern. While the literature examining the topic is vast, few studies look at entrepreneurship in particular. Our work contributes to this literature by estimating how disasters affect entrepreneurs in the U.S. states, the first study at this level of aggregation, while considering alternative forms of entrepreneurial activity, which helps address an important gap in the literature. We find that disaster effects vary significantly by entrepreneurship type, a result with implications for economic dynamism and public policy.

Although our state-level data improve on prior country-level work, they may be too coarse to describe events impacting various regions of a state differently. That said, Dolfman et al. (2007) and Nielsen-Pincus et al. (2013) find that disaster effects are felt statewide, meaning granular data at county- or municipality-level may fail to capture the full impact. As for the Kauffman Indicators as a measure of entrepreneurial outcomes, previous studies examining topics such as adversity and resilience for individual entrepreneurs through a qualitative lens, although insightful, does not have the requisite external validity.

The study offers a number of exciting avenues for future research. For example, the precise impact of federal assistance in the aftermath of natural disasters is not fully understood, although previous studies suggest that it is stimulatory; in the present context, we consider it unlikely that a favorable entrepreneurship effect would emerge in the absence of large public aid and look forward to future work exploring this channel. Further, given that disasters typically cause within- and out-of-state migration, it is worthwhile to analyze where new start-ups are located, which would clarify whether the positive impact only appears in disaster areas or spills over into nearby regions.

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Tables

Table 1. Kauffman Indicators by U.S. State, 1998-2018

State	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
Alabama	-1.4419	0.0021	0.7620	4.7195	0.7922
Arizona	0.4063	0.0037	0.7959	6.1629	0.7690
Arkansas	-0.1309	0.0033	0.8070	5.0152	0.7762
California	1.1592	0.0039	0.7870	7.1052	0.7905
Colorado	1.0751	0.0039	0.8173	6.8071	0.7788
Connecticut	-0.7612	0.0025	0.7866	4.2829	0.8030
Delaware	-0.6921	0.0020	0.8629	6.7052	0.7820
Florida	0.7303	0.0035	0.8151	7.9695	0.7720
Georgia	0.3106	0.0035	0.7971	6.0471	0.7779
Idaho	0.8790	0.0039	0.8143	6.4371	0.7738
Illinois	-1.0599	0.0024	0.7847	4.9476	0.7881
Indiana	-0.9753	0.0024	0.7985	4.4952	0.7895
Iowa	-0.0787	0.0026	0.8524	4.1795	0.8088
Kansas	0.0230	0.0027	0.8474	5.9619	0.7911
Kentucky	-0.6374	0.0027	0.8010	4.6505	0.7865
Louisiana	0.1480	0.0033	0.8090	5.8457	0.7804
Maine	0.0873	0.0033	0.7986	4.6129	0.7947
Maryland	-0.7580	0.0029	0.7762	5.1757	0.7748
Massachusetts	-0.4508	0.0024	0.7654	5.3819	0.8200
Michigan	-0.7806	0.0024	0.7940	5.4105	0.7897
Minnesota	-0.1874	0.0025	0.7975	5.5229	0.8120
Mississippi	-0.3514	0.0033	0.7817	4.4738	0.7751
Missouri	-0.3469	0.0027	0.8086	5.2686	0.7964
Montana	2.3088	0.0048	0.8379	5.7005	0.7942
Nebraska	0.3472	0.0029	0.8932	4.9948	0.7947
Nevada	0.2163	0.0033	0.7867	7.4819	0.7694
New Hampshire	-1.4152	0.0025	0.7989	4.4624	0.7627
New Jersey	-0.2198	0.0026	0.8094	7.2438	0.7825
New Mexico	0.6062	0.0041	0.7966	5.6319	0.7619
New York	0.7027	0.0032	0.8172	7.1429	0.7963
North Carolina	-0.1546	0.0029	0.7937	5.4738	0.7968
North Dakota	0.6160	0.0032	0.8503	5.6610	0.7970
Ohio	-1.0546	0.0023	0.7979	4.3981	0.7943
Oklahoma	0.9748	0.0035	0.8380	6.3310	0.7905
Oregon	-0.0423	0.0034	0.7855	5.3490	0.7760
Pennsylvania	-1.4676	0.0017	0.8024	4.4729	0.8040
Rhode Island	-2.1812	0.0020	0.7519	4.6057	0.7668
South Carolina	-0.4210	0.0026	0.8053	5.4752	0.7977
South Dakota	1.0681	0.0034	0.8838	4.7110	0.8084
Tennessee	-0.5990	0.0028	0.7956	5.2514	0.7814
Texas	0.7542	0.0037	0.7941	6.0548	0.7911
Utah	0.3339	0.0031	0.8415	7.1981	0.7702
Vermont	0.3893	0.0038	0.7815	4.2343	0.7874
Virginia	-1.0991	0.0023	0.7958	5.5129	0.7814
Washington	-1.4169	0.0027	0.8008	5.0943	0.7411
West Virginia	-1.4870	0.0019	0.8504	3.7819	0.7825
Wisconsin	-0.7083	0.0025	0.7719	4.2376	0.8140
Wyoming	1.0314	0.0037	0.8637	6.1100	0.7788

Note. All values are annual averages for 1998-2018.

Table 2. Natural Disasters by U.S. State, 1998-2018

State	Crop Damage	Property Damage	Crop Damage Duration	Property Damage Duration	Records
Alabama	4,779,905	597,898,368	4	20	513
Arizona	1,230,738	201,326,304	1	7	141
Arkansas	11,911,089	223,185,360	15	13	374
California	389,746,752	1,478,904,064	9	20	353
Colorado	8,001,059	355,193,888	4	14	130
Connecticut	2,154	12,162,901	0	2	64
Delaware	2,097,659	8,450,011	1	2	37
Florida	345,191,808	2,646,565,888	5	13	404
Georgia	173,425,136	210,867,392	6	8	694
Idaho	4,429,918	37,859,640	3	12	84
Illinois	84,943,168	201,389,648	16	18	394
Indiana	47,444,980	105,502,352	12	19	338
Iowa	401,271,072	577,041,408	17	15	958
Kansas	37,577,676	160,703,568	10	5	320
Kentucky	19,736,478	106,520,888	8	11	465
Louisiana	78,978,760	3,732,921,856	10	10	312
Maine	4,093	30,836,550	0	3	41
Maryland	5,094,184	67,736,760	4	3	210
Massachusetts	68,649	41,535,896	0	4	208
Michigan	22,924,998	258,612,352	3	9	295
Minnesota	12,638,952	164,258,128	5	12	162
Mississippi	97,589,584	1,700,768,256	9	8	680
Missouri	23,428,804	385,842,976	18	16	366
Montana	2,628,286	16,153,620	3	8	77
Nebraska	134,699,968	129,550,280	9	12	335
Nevada	3,300	18,826,204	0	7	83
New Hampshire	11,558	12,745,253	0	3	43
New Jersey	6,365,037	1,374,735,488	2	9	184
New Mexico	1,494,555	135,982,544	2	12	106
New York	10,575,476	220,579,456	3	10	665
North Carolina	163,277,856	510,321,952	21	4	403
North Dakota	27,532,152	86,070,688	4	13	119
Ohio	23,891,958	248,701,488	3	6	771
Oklahoma	95,416,448	385,203,904	27	26	374
Oregon	2,990,004	19,319,064	2	7	69
Pennsylvania	35,794,912	139,632,752	3	4	555
Rhode Island	0	6,982,162	0	2	26
South Carolina	35,830,576	47,972,776	1	4	314
South Dakota	3,130,523	27,466,028	2	9	104
Tennessee	1,239,579	329,050,432	4	6	572
Texas	706,916,032	5,635,924,992	42	38	1143
Utah	221,173	84,008,072	1	10	133
Vermont	1,855,760	76,486,008	1	5	232
Virginia	31,891,566	108,224,952	6	4	662
Washington	33,120,342	263,909,600	5	14	140
West Virginia	762,102	59,633,708	3	4	279
Wisconsin	42,836,024	225,468,688	9	14	323
Wyoming	278,010	10,918,955	1	8	56

Note. All values are annual averages for 1998-2018. Damages are in 2015 U.S. dollars.

Table 3. Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Entrepreneurial Activity					
Summary Index of Entrepreneurs	1,008	1.7733	0.3922	1.0762	4.3311
Rate of New Entrepreneurship	1,008	0.0029	0.0007	0.0012	0.0060
Opportunity Share of New Entrepreneurs	1,008	0.8084	0.0622	0.5569	0.9484
Start-Up Early Job Creation	1,008	5.4956	1.5544	2.7200	15.8700
Start-Up Early Survival Rate	1,008	0.7863	0.0278	0.6698	0.9158
Control Variables					
Establishments (1,000s)	960	153	159	18	941
Firms (1,000s)	960	124	130	16	764
Employment (1,000s)	960	2,411	2,520	164	14,907
Commercial Banks	1,006	142	139	4	799
Commercial Bank Assets ($)	1,006	249,908	504,943	2,149	3,035,700
Commercial Bank Deposits ($)	1,006	178,023	354,663	1,807	2,290,543
Commercial Bank Equity ($)	1,006	25,934	50,661	223	301,855
Commercial Bank Net Income ($)	1,006	2,400	5,210	-25,250	37,521
Population (1,000s)	1,008	6,257	6,740	490	39,461
Prime-Age Population (1,000s)	1,008	3,987	4,301	318	24,823
Personal Income ($)	1,008	251,587	307,785	12,471	2,500,000
Natural Disasters					
Crop Damage ($)	1,006	65	277	0	3,000
Property Damage ($)	1,006	490	3,784	57	85,319
Crop Damage Duration (days)	1,006	7	23	0	382
Property Damage Duration (days)	1,006	10	23	1	382
Records	1,006	320	293	3	1,924

Note. All dollar-based variables are in 2015 U.S. dollars (millions).

Table 4. Estimates for Total Damages Scaled by State Population

	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
$D_{t=0}$	0.000	0.003	0.002	-0.000	0.000
	(0.003)	(0.006)	(0.003)	(0.004)	(0.001)
$\sum_{t=0}^{1} D_t$	0.003	0.010	-0.001	0.004	-0.003***
	(0.003)	(0.015)	(0.003)	(0.004)	(0.001)
$\sum_{t=0}^{2} D_t$	0.006	0.021	0.001	0.008	-0.004***
	(0.005)	(0.014)	(0.003)	(0.006)	(0.001)
$\sum_{t=0}^{3} D_t$	0.001	0.032*	0.001	0.001	-0.004***
	(0.005)	(0.019)	(0.004)	(0.007)	(0.002)
$\sum_{t=0}^{4} D_t$	0.011*	0.033***	-0.007**	0.016*	-0.005**
	(0.006)	(0.009)	(0.003)	(0.008)	(0.002)
$\sum_{t=0}^{5} D_t$	0.012	0.039***	-0.011***	0.019*	-0.008***
	(0.009)	(0.012)	(0.004)	(0.011)	(0.003)
State fixed effects?	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes	Yes
Number of clusters	48	48	48	48	48

Note. Models are estimated using least squares with state and year fixed effects. Coefficients report the joint estimate for disaster damages D scaled by state population where t is the number of lags for damages. We include the first lag of dependent variable and all controls, which are omitted in the table. Standard errors are clustered at state level and robust to heteroscedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Estimates for Total Damages Scaled by State Income

	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
$D_{t=0}$	-0.005	0.114	0.079	-0.024	0.009
	(0.095)	(0.200)	(0.117)	(0.132)	(0.022)
$\sum_{t=0}^{1} D_t$	0.080	0.399	-0.016	0.112	-0.099***
	(0.123)	(0.516)	(0.122)	(0.163)	(0.033)
$\sum_{t=0}^{2} D_t$	0.201	0.780	0.034	0.256	-0.129***
	(0.172)	(0.491)	(0.091)	(0.219)	(0.039)
$\sum_{t=0}^{3} D_t$	0.013	1.145*	0.034	0.016	-0.134***
	(0.187)	(0.634)	(0.136)	(0.252)	(0.047)
$\sum_{t=0}^{4} D_t$	0.358	1.132***	-0.266**	0.523*	-0.154**
	(0.226)	(0.287)	(0.114)	(0.287)	(0.064)
$\sum_{t=0}^{5} \mathrm{D}_t$	0.415	1.352***	-0.400***	0.671*	-0.256***
	(0.296)	(0.392)	(0.126)	(0.377)	(0.083)
State fixed effects?	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes	Yes
Number of clusters	48	48	48	48	48

Note. Models are estimated using least squares with state and year fixed effects. Coefficients report the joint estimate for disaster damages D scaled by state income where t is the number of lags for damages. We include the first lag of dependent variable and all controls, which are omitted in the table. Standard errors are clustered at state level and robust to heteroscedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Estimates for Total Damages Scaled by State Population, Controlling for Crop Insurance

	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
$D_{t=0}$ x CI	-0.000	0.004	0.002	-0.001	0.000
	(0.003)	(0.006)	(0.003)	(0.004)	(0.001)
$\sum_{t=0}^{1} D_t$ x CI	0.002	0.010	-0.002	0.003	-0.003***
	(0.004)	(0.014)	(0.003)	(0.005)	(0.001)
$\sum_{t=0}^{2} D_t$ x CI	0.005	0.022	-0.001	0.006	-0.004***
	(0.005)	(0.015)	(0.002)	(0.006)	(0.001)
$\sum_{t=0}^{3} D_t$ x CI	0.018**	0.046***	0.006	0.025**	-0.008***
	(0.008)	(0.017)	(0.004)	(0.011)	(0.003)
$\sum_{t=0}^{4} D_t$ x CI	0.026***	0.057***	-0.003	0.038***	-0.011***
	(0.010)	(0.014)	(0.005)	(0.013)	(0.004)
$\sum_{t=0}^{5} D_t$ x CI	0.020	0.071***	-0.009	0.033*	-0.014***
	(0.015)	(0.016)	(0.006)	(0.019)	(0.004)
State fixed effects?	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes	Yes
Number of clusters	48	48	48	48	48

Note. Models are estimated using least squares with state and year fixed effects. Coefficients report the joint estimate for disaster damages D scaled by state population, including interactions with crop insurance, where t is the number of lags for damages. We include the first lag of dependent variable and all controls, which are omitted in the table. Standard errors are clustered at state level and robust to heteroscedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Estimates for Total Damages Scaled by State Income, Controlling for Crop Insurance

	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
$D_{t=0}$ x CI	-0.015	0.131	0.078	-0.038	0.008
	(0.091)	(0.192)	(0.118)	(0.127)	(0.023)
$\sum_{t=0}^{1} D_t$ x CI	0.031	0.352	-0.070	0.065	-0.110***
	(0.143)	(0.495)	(0.125)	(0.187)	(0.042)
$\sum_{t=0}^{2} D_t$ x CI	0.145	0.759	-0.018	0.215	-0.154***
	(0.188)	(0.513)	(0.090)	(0.232)	(0.047)
$\sum_{t=0}^{3} D_t$ x CI	0.896***	1.670***	0.246*	1.288***	-0.347***
	(0.299)	(0.638)	(0.145)	(0.404)	(0.127)
$\sum_{t=0}^{4} D_t$ x CI	1.153***	2.164***	-0.083	1.681***	-0.499***
	(0.410)	(0.626)	(0.216)	(0.523)	(0.190)
$\sum_{t=0}^{5} D_t$ x CI	0.861	2.847***	-0.268	1.412*	-0.580***
	(0.609)	(0.686)	(0.234)	(0.772)	(0.186)
State fixed effects?	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes	Yes
Number of clusters	48	48	48	48	48

Note. Models are estimated using least squares with state and year fixed effects. Coefficients report the joint estimate for disaster damages D scaled by state income, including interactions with crop insurance, where t is the number of lags for damages. We include the first lag of dependent variable and all controls, which are omitted in the table. Standard errors are clustered at state level and robust to heteroscedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Estimates for Total Damages Scaled by State Population, Controlling for Crop Insurance, Excluding Lagged Dependent Variable

	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
$D_{t=0}$ x CI	-0.000	-0.001	0.002	-0.001	0.000
	(0.003)	(0.003)	(0.004)	(0.005)	(0.001)
$\sum_{t=0}^{1} D_t$ x CI	0.000	0.003	-0.005	0.001	-0.003**
	(0.005)	(0.014)	(0.005)	(0.007)	(0.001)
$\sum_{t=0}^{2} D_t$ x CI	0.004	0.016	-0.006	0.006	-0.005***
	(0.007)	(0.020)	(0.005)	(0.008)	(0.001)
$\sum_{t=0}^{3} D_t$ x CI	0.020**	0.049**	-0.005	0.029**	-0.009***
	(0.010)	(0.024)	(0.007)	(0.013)	(0.003)
$\sum_{t=0}^{4} D_t$ x CI	0.033***	0.080***	-0.015**	0.049***	-0.013***
	(0.012)	(0.022)	(0.007)	(0.015)	(0.005)
$\sum_{t=0}^{5} D_t$ x CI	0.032*	0.107***	-0.027***	0.051**	-0.015***
	(0.017)	(0.024)	(0.006)	(0.021)	(0.005)
State fixed effects?	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes	Yes
Number of clusters	48	48	48	48	48

Note. Models are estimated using least squares with state and year fixed effects. Coefficients report the joint estimate for disaster damages D scaled by state population, including interactions with crop insurance, where t is the number of lags for damages. We include all controls, which are omitted in the table. Standard errors are clustered at state level and robust to heteroscedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Estimates for Total Damages Scaled by State Income, Controlling for Crop Insurance, Excluding Lagged Dependent Variable

	Summary Index of Entrepreneurs	Rate of New Entrepreneurs	Opportunity Share of New Entrepreneurs	Start-Up Early Job Creation	Start-Up Early Survival Rate
$D_{t=0}$ x CI	-0.022	-0.026	0.081	-0.051	0.014
	(0.118)	(0.097)	(0.127)	(0.164)	(0.020)
$\sum_{t=0}^{1} D_t$ x CI	-0.025	0.107	-0.165	-0.003	-0.106**
	(0.183)	(0.513)	(0.184)	(0.241)	(0.045)
$\sum_{t=0}^{2} D_t$ x CI	0.113	0.586	-0.213	0.190	-0.177***
	(0.241)	(0.728)	(0.165)	(0.298)	(0.055)
$\sum_{t=0}^{3} D_t$ x CI	0.982**	1.846**	-0.191	1.447***	-0.384***
	(0.406)	(0.819)	(0.246)	(0.545)	(0.147)
$\sum_{t=0}^{4} D_t$ x CI	1.490***	3.079***	-0.608**	2.209***	-0.547***
	(0.505)	(0.795)	(0.272)	(0.637)	(0.212)
$\sum_{t=0}^{5} D_t$ x CI	1.360**	4.205***	-1.064***	2.168**	-0.637***
	(0.681)	(0.956)	(0.250)	(0.849)	(0.214)
State fixed effects?	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes	Yes
Number of clusters	48	48	48	48	48

Note. Models are estimated using least squares with state and year fixed effects. Coefficients report the joint estimate for disaster damages D scaled by state income, including interactions with crop insurance, where t is the number of lags for damages. We include all controls, which are omitted in the table. Standard errors are clustered at state level and robust to heteroscedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 1: Summary Index of Entrepreneurs by U.S. State, Annual Average for 1998-2018

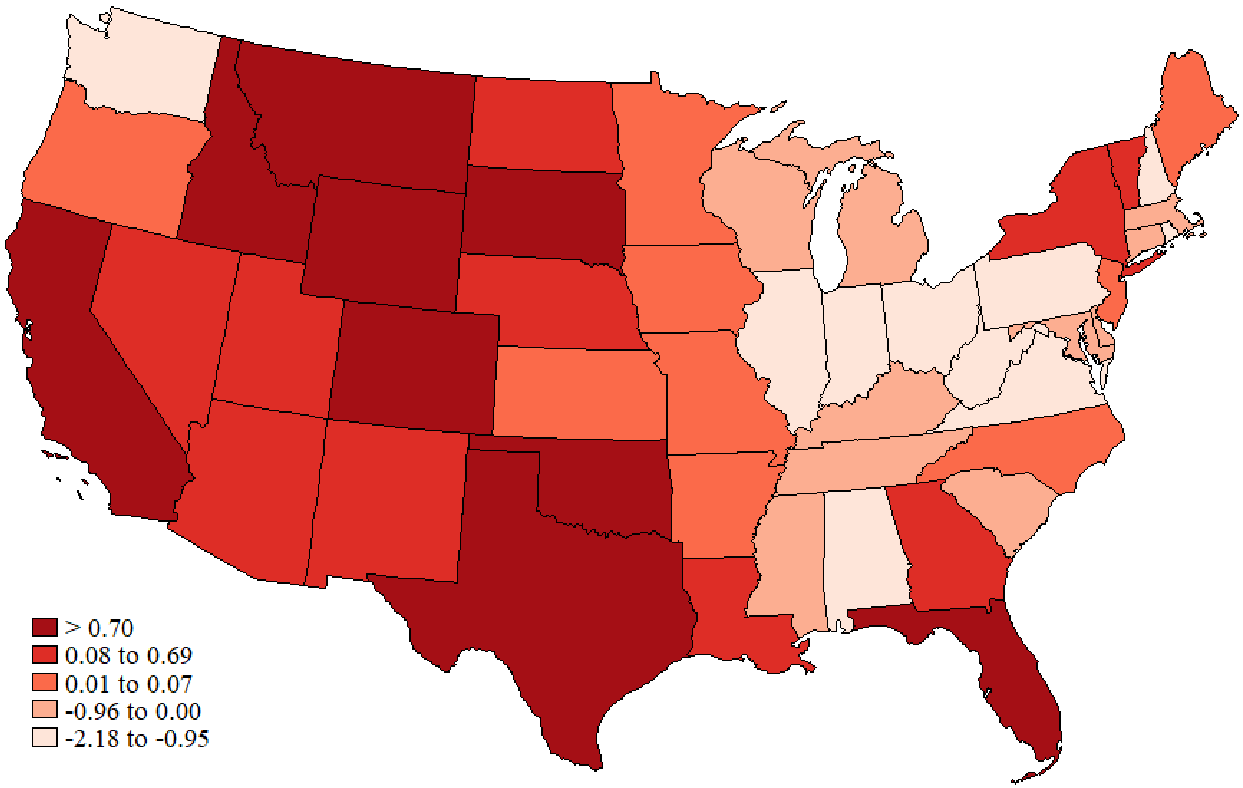

Figure 2: Total Disaster Damage by U.S. State, Annual Average for 1998-2018