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When shocks repeat: Recurrent disasters, recombination capacity and entrepreneurial regeneration

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Research Article

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Abstract

Entrepreneurs increasingly face adversity that recurs before recovery is complete, yet research on entrepreneurship and crises has mostly examined isolated shocks. We ask how repeated shocks change local entrepreneurial regeneration and which endogenous local capacities are associated with it. We introduce endogenous resource recombination capacity (ERRC), the capacity of a local economy to recombine the resources that remain after a shock, and distinguish its agents (a base of young firms) from its raw material (the variety of local activities). Linking federal major disaster declarations for natural hazards in 3,119 U.S. counties between 2000 and 2023 to Census business dynamics, we estimate local projections that separate isolated from repeated shocks. Isolated disasters are followed by a modest rise in establishment entry and repeated disasters by higher exit. Shocks preceded by declarations in three or more of the previous five years are followed by lower startup, entry and net job creation rates, also when the hazard-proneness of counties is controlled for. Exploratory analyses suggest that the local characteristics associated with post-shock startups differ by shock history. After isolated shocks, startups rise more where the young-firm base is larger, but this association largely reflects scale. After repeated shocks without federal assistance to households, startups fall less where sectoral variety is greater; this association survives scale and severity checks but is sensitive to the measure of variety, to long-difference specifications and to restricting shocks to hurricanes and floods. Sustaining entrepreneurship under recurrent adversity may require capacities built between shocks.

JEL classification:L26; Q54; R11; H84

Plain English Summary

Repeated disasters wear local entrepreneurship down rather than toughen it. Comparing 3,119 U.S. counties between 2000 and 2023, we find that a disaster after a quiet period is followed by slightly more business openings, whereas disasters that follow earlier ones are followed by more closures, and those that follow disasters in three or more of the previous five years by fewer startups and openings. After repeated disasters, startups also fall less where employment is spread more evenly across sectors, although this pattern is less certain. For places hit again and again, support for local businesses between disasters and a varied local economy may also matter, not only emergency help after each event.

1 Introduction

Research on entrepreneurship and crises has largely studied adversity as an episode: a shock strikes, entrepreneurs and their communities respond, and recovery follows (Doern et al., 2019; Williams et al., 2017). For a growing number of places this sequence no longer describes reality. Floods, storms and fires return before recovery from the previous event is complete, so that impacts overlap and interact (de Ruiter et al., 2020). Entrepreneurs in such places face adversity as a condition rather than an event, and the external support that helps them through a single crisis, from disaster aid to ecosystem services, may be depleted or simply absent when the next shock arrives. In a study of founders in a context of permanent crisis, Audretsch and Kariv (2025) find that ecosystem support has no significant direct effect on performance, while psychological capital and community belonging do; related work examines the interplay of grit and community belonging in polycrisis (Audretsch & Kariv, 2026). This raises the question at the heart of the special issue: which endogenous capacities sustain entrepreneurship when support from outside fails, and do they work in the same way when adversity recurs?

Two literatures offer partial answers. Studies of entrepreneurial resilience emphasise what entrepreneurs do with the resources at hand: making do by recombining what others ignore (Baker & Nelson, 2005), finding ways around constraints (Williams et al., 2021) and creating ventures that help communities recover after disasters (Shepherd & Williams, 2014; Williams & Shepherd, 2016). Research on regional resilience emphasises the structure of places: the variety of industries that can absorb a shock and provide resources for new growth paths (Boschma, 2015; Frenken et al., 2007; Martin & Sunley, 2015). A recent county-level study connects the two, showing that higher shares of young and small firms reduce employment losses after extreme weather events (Heinzel et al., 2025). These literatures, however, mostly ask which

resources or structures a place possesses when a shock occurs. They rarely ask whether the capacities that sustain entrepreneurship after one shock are the same that sustain it after the third.

We argue that they need not be. We introduce endogenous resource recombination capacity (ERRC), the capacity of a local economy to recombine the resources that remain after a shock into new ventures, and distinguish two constituents: recombining agents, a base of young firms that can convert disruption into entry, and recombinable resources, the variety of local activities on which entrepreneurs can draw. Our conjecture is that repeated adversity changes the source of entrepreneurial regeneration. After an isolated shock, slack and external support are largely intact, and regeneration should depend on the agents. When shocks recur and support is absent, slack is eroded, the entrepreneurial base thins, and regeneration should come to depend on the variety of resources available.

We examine this argument with public data on 3,119 U.S. counties, linking federal major disaster declarations for natural hazards between 2000 and 2023 to the Census Business Dynamics Statistics and Business Formation Statistics. Disasters are frequent: the average county had a declaration in six of the 24 years, and 80% of these county-years followed a declaration in the previous five years. Using local projections that separate isolated from repeated shocks, we document a consistent pattern and an exploratory one. The consistent pattern is erosion, which is clearest for shocks that follow many others. Isolated disasters are followed by a modest rise in establishment entry, repeated disasters by higher exit, and shocks preceded by declarations in three or more of the previous five years by lower startup, entry and net job creation rates, also when we control for the long-run hazard-proneness of counties. The exploratory pattern concerns ERRC: the young-firm base is associated with larger rises in startups after isolated shocks, largely because such places have higher startup rates, and sectoral variety with smaller declines after repeated shocks without federal assistance to households, an association that is sensitive to how variety is measured and to the specification. A composite capacity index hides these different patterns.

The study makes three contributions. It brings the temporal structure of adversity into research on entrepreneurial resilience, showing that the entrepreneurial response to a disaster depends on how many came before. It proposes ERRC as a configuration of agents and raw material and offers initial evidence that its constituents are associated with regeneration under different conditions, which composite measures conceal. And it qualifies the expectation that endogenous capacities substitute for external support: variety is associated with smaller post-shock declines only after repeated shocks without federal assistance to households, while the young-firm base shows the opposite pattern. We state which results are robust and which are exploratory, and we provide code that reproduces every estimate from public data.

2 Theory and hypotheses

2.1 From isolated shocks to recurrent adversity

Crisis research distinguishes crisis as an event from crisis as a process, and resilience as the capacity to absorb, adjust to and learn from disturbances over time (Williams et al., 2017). Entrepreneurship research has nevertheless studied mainly single events, whose aftermath can create opportunities as well as losses. After the 2010 Haiti earthquake, locally founded ventures either sustained victims or helped them build autonomy (Williams & Shepherd, 2016), and after an Australian bushfire, local ventures connected affected communities to resources in the wider community and delivered rapid, tailored aid (Shepherd & Williams, 2014). Disasters have direct effects through damage and indirect effects on economic activity (Botzen et al., 2019), and small and less productive establishments are least likely to survive, in part because of financial constraints (Basker & Miranda, 2018); disaster loans help small businesses survive floods (Davlasheridze & Geylani, 2017).

Recurrent adversity changes this picture in three ways. First, each shock draws down the slack of firms and households, such as savings, credit and spare capacity, which may not be rebuilt before the next one. Second, external support is episodic. Federal disaster assistance follows declarations whose scope, and partly whose occurrence, varies with severity and with politics (Garrett & Sobel, 2003), and support mobilised after one event does not guarantee support after the next. Third, recurrence changes expectations. Expected flood risk reduces firm entry substantially in U.S. counties, while individual flood events have limited effects on entry (Jia et al., 2026). Regional research describes such persistent effects as hysteresis

(Martin, 2012), and in peripheral places historical legacies can constrain entrepreneurial ambition and local economic resilience (Gherhes et al., 2018). Context, in short, includes time: entrepreneurship takes place in historical and temporal as well as spatial and institutional settings (Welter, 2011; Welter et al., 2019).

2.2 Endogenous resource recombination capacity

We define endogenous resource recombination capacity (ERRC) as the capacity of a local economy to recombine the resources that remain after a shock into new ventures. The concept extends combinative capabilities, the capacity of firms to create new capabilities by recombining existing knowledge (Kogut & Zander, 1992), and entrepreneurial bricolage, making do by recombining resources at hand (Baker & Nelson, 2005), from firms to places. It differs from resilience, which denotes maintaining or recovering functioning, and from resourcefulness, which denotes finding ways around constraints (Williams et al., 2021), because it concerns the reconfiguration of local resource combinations after successive shocks, with decreasing dependence on support from outside.

Recombination requires agents and raw material. The agents are entrepreneurs and young firms. Young firms account for a disproportionate share of job creation (Haltiwanger et al., 2013), and their presence reduces employment losses after extreme weather (Heinzel et al., 2025). A large young-firm base signals a local population of people who found and run businesses, with the skills and networks to turn disruption into entry. The raw material is the variety of local activities, which can play two roles. Variety across unrelated sectors acts mainly as a portfolio that buffers sector-specific shocks, whereas related variety provides the spillovers through which skills and knowledge are recombined into new activities (Frenken et al., 2007); both are seen as sources of regional resilience (Boschma, 2015). A varied local economy thus offers both protection and a wider set of inputs, skills and customers on which entrepreneurs can draw. The two constituents need not move together: a place can have many young firms in a narrow economy, or a varied economy with few young firms. ERRC is thus a configuration, and its constituents may matter under different conditions.

2.3 Hypothesis and exploratory expectations

Our main hypothesis concerns the entrepreneurial response to shocks. After an isolated shock, slack and external support allow entrepreneurs to exploit the opportunities that disruption creates, such as rebuilding, replacement demand and gaps left by exiting firms. As shocks accumulate, slack is drawn down, exits rise and expected future losses discourage new entry.

Hypothesis (erosion). The post-shock entrepreneurial response weakens with the number of recent shocks: entry falls and exit rises as shocks accumulate.

The ERRC argument also implies expectations about which constituent matters under which conditions. Because we sharpened them after the first estimates with a composite index (Section 3.4), we state them as exploratory expectations rather than as hypotheses that the design was built to test. The first concerns the agents of regeneration after an isolated shock. When slack and support are intact, the main constraint on regeneration is the presence of people able to act on post-disaster opportunities. Places with a larger young-firm base have more of them.

Exploratory expectation 1 (agent-driven regeneration). After an isolated shock, post-shock entry rises more where the local young-firm base is larger.

Repeated shocks change this relation. Small, financially constrained establishments are the least likely to survive a disaster (Basker & Miranda, 2018). If young firms face similar constraints, repeated losses without support may deplete the base that sustains regeneration after a single shock. What remains are the resources of the place: the variety of activities, inputs and skills that entrepreneurs can recombine in new ways, as bricoleurs do with resources others ignore (Baker & Nelson, 2005). Under recurrence, regeneration should therefore depend less on the agents and more on the raw material of recombination.

Exploratory expectation 2 (shift to recombinable resources). After repeated shocks, the positive association between the young-firm base and post-shock entry weakens, and post-shock entry rises more where local resources are more varied.

The third expectation addresses external support. If endogenous capacities substitute for support from outside, as may happen when ecosystems fail (Audretsch & Kariv, 2025), they should matter most when a shock is not accompanied by external assistance.

Exploratory expectation 3 (substitution). The association between ERRC and post-shock entry is stronger when a shock is not accompanied by federal assistance to households.

Fig. 1 summarises the framework. The erosion hypothesis and the general expectation that ERRC moderates post-shock entry guided the design from the start; the three exploratory expectations refine the second part of the argument.

Figure 1 Conceptual framework: isolated and repeated shocks, the constituents of endogenous resource recombination capacity (ERRC) and post-shock entrepreneurial regeneration. H denotes the erosion hypothesis and E1–E3 the exploratory expectations in Section 2.3; the dashed box marks federal assistance to households, which Exploratory expectation 3 expects to weaken the role of ERRC

3 Data and methods

3.1 Data and sample

We combine three public sources at the county-year level. Shocks come from the OpenFEMA Disaster Declarations Summaries (Federal Emergency Management Agency, n.d.), which list every county designated in a federal declaration and have been widely used to measure disaster exposure in U.S. counties (Boustan et al., 2020). We keep major disaster declarations for natural hazards, excluding biological events (including COVID-19), human-caused and other non-natural incidents, and designations that refer to a whole state rather than a county (1.4% of natural-hazard designations in 2000–2023). The shock year is the year in which the incident began. Entrepreneurial outcomes come from the county files of the Business Dynamics Statistics (U.S. Census Bureau, n.d.; 2023 release), which measure annual changes between the March pay periods of consecutive years for all employer establishments and firms, including tabulations by firm age and by sector. Business applications come from the county Business Formation Statistics (BFS), which count applications for an employer identification number from 2005 onwards (U.S. Census Bureau, 2026). We drop the BDS statewide pseudo-units and Connecticut, which the 2023 BDS release codes by planning regions that cannot be linked to FEMA county designations, and we assign FEMA designations for four counties whose codes changed to the codes used by the BDS. The sample comprises 3,119 counties with BDS data for the baseline period 1995–1999, observed from 2000 to 2023 (74,856 county-years). Descriptive statistics (Table 1) use all years; estimation uses shock years 2000–2020 (Section 3.3).

3.2 Measures

Shocks and shock history. A county experiences a shock in year t if it was designated in at least one major disaster declaration whose incident began in t. A shock is *repeated* if the county had at least one shock in the previous five years ($t - 5$ to $t - 1$), and *isolated* otherwise. To trace the dose of adversity we also count the years with shocks in the previous five years (0, 1, 2, 3 or more). A shock is *assisted* if at least one declaration in t designated the county for federal assistance to individuals and households (Individual Assistance or the Individuals and Households Program). Assistance signals both greater damage to households and external support beyond public infrastructure; we cannot separate the two, and we interpret differences between assisted and unassisted shocks with this in mind.

Outcomes. The primary outcome is the startup rate, the number of firms of age zero per 100 firms in the county. Secondary outcomes are the establishment entry rate, the job creation rate from establishment births, the establishment exit rate and the net job creation rate, all from the BDS, and the logarithm of business applications from the BFS. Establishment entry includes new establishments of existing firms, so the startup rate is the closest measure of new firm formation. For each shock year we average each outcome over the three following years ($t + 1$ to $t + 3$), which avoids attributing to the shock changes that occurred before the incident within the BDS reference year.

Endogenous resource recombination capacity. We measure the two constituents of ERRC in 1995–1999, before the analysis period (Online Resource 1, Tables S1 and S7). The *young-firm base* is the share of county employment in firms aged zero to five years. *Sectoral variety* is the Shannon entropy of employment across the 19 two-digit NAICS sectors (Frenken et al., 2007); cells suppressed for disclosure (13% of sector-county-years) are excluded from the shares. Because the sectors are broad, this measure captures variety across largely unrelated activities, and it cannot separate the portfolio and recombination roles of variety discussed in Section 2.2. Both measures are winsorized at the 1st and 99th percentiles and standardized across counties. Their correlation is − 0.08, so a place can be rich in one and poor in the other. Variety rises with county size (correlation with baseline log employment 0.64), and the young-firm base is correlated with the baseline startup rate (0.54), which we address with size interactions and scale checks.

3.3 Estimation

We estimate local projections (Jordà, 2005) of the post-shock outcome on indicators of the shock condition. The main models (Table 2) are, for county *i* in state *s* and shock year *t*:

$$\bar{Y}_{i,t+1:t+3} = \Sigma_c \beta_c D_{it} C_{c,it} + \Sigma_{k\neq 0} \varphi_k D_{i,t+k} + \alpha_i + \theta_{st} + \varepsilon_{it}$$

where $\bar{Y}$ is the post-shock average of the outcome, D_{it} indicates a shock and $C_{c,it}$ indicates its condition *c* (isolated or repeated; or the number of prior years with shocks). The terms $D_{i,t+k}$ control for shocks in every other year from *t* − 5 to *t* + 3, county fixed effects α_i absorb time-invariant differences, including the levels of the capacity measures, and state-by-year fixed effects θ_{st} absorb state-wide business cycles and policy. The capacity models (Table 3) add, for each condition, interactions of $D_{it}C_{c,it}$ with the young-firm base Y_i, sectoral variety V_i and centered baseline log employment S_i, and an indicator R_{it} for shocks in the previous five years, whether or not a shock occurs in *t*, with its interactions with Y_i, V_i and S_i. R_{it} ensures that the lasting associations of past shocks with the outcome, and their variation with capacity, are not attributed to the current shock. Standard errors are clustered by county. Shock years run from 2000 to 2020, so that every post-shock window ends by 2023 (from 2004 for business applications). To examine dynamics, we estimate the isolated/repeated model of Table 2 for each year from *t* − 3 to *t* + 4, with shock years 2000–2019 at every horizon and controls for shocks from *t* − 5 to *t* + *h* (to *t* − 1 for *h* ≤ 0), and we test the capacity models on the outcome at *t* − 2 and *t* − 1.

Declarations are recurrent and non-absorbing, and their effects may vary with shock history. Two-way fixed effects event studies can be biased in such settings (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Sun & Abraham, 2021). Our local projections give each shock condition its own coefficient, but they still use county-years that were or will be treated as comparisons. We therefore also estimate long-difference versions, in which the outcome is the post-shock average minus its value in *t* − 1, as in the local-projection approach to difference-in-differences (Dube et al., 2025), and versions that also drop county-years with shocks in *t* + 1 to *t* + 3. These variants move towards, but do not fully implement, the clean-control rule of that approach.

The timing of disasters is plausibly unrelated to local entrepreneurial trends once county and state-by-year fixed effects are included, but declarations are not purely natural events: their occurrence and scope also reflect politics (Garrett & Sobel, 2003). Repeated shocks also occur in places that are more exposed to hazards. We address these concerns by comparing shocks within the same state and year, testing for differences before the shock, restricting treated county-years to hurricanes and floods, adding severity controls (interactions of the shock with a hurricane indicator and with two or more declarations in *t*), and interacting the shock with the county's hazard-proneness, the standardized number of years with declarations in 1980–1999.

3.4 Analysis sequence

The analysis was not pre-registered. The initial design compared isolated and repeated shocks and interacted them with a composite ERRC index, the standardized sum of the standardized young-firm base and sectoral variety. We estimated this composite model first, by shock history and by assistance (Online Resource 1, Table S6); the model by assistance pools isolated and repeated shocks and does not include the recent-shock indicator R. We then estimated the two constituents

separately and crossed shock history with assistance, as in Table 3. These models were specified after the composite results were known and involve many coefficients (several outcomes, four shock conditions and two constituents), so their *p*-values should be read as exploratory, and we state the corresponding expectations as exploratory (Section 2.3). We also report Benjamini–Hochberg false discovery rate *q*-values for these tests (Online Resource 1, Table S8). We report all of them, with formal contrasts, scale checks and robustness tests (Table 4 and Online Resource 1).

3.5 Use of a large language model

The study was carried out with the assistance of a large language model, Claude Opus 5.5 (Anthropic; model identifier claude-opus-5-5, October 2026). The research question, the ERRC concept and the initial design came from the author. Under the author's direction, the model wrote and ran the code that assembles the data and estimates the models, searched for and checked the literature, and drafted the text, tables and figures. The outputs were validated in four ways. The full pipeline was re-run from the raw public files in a clean environment and reproduced every estimate and table exactly. The fixed-effects estimator, implemented directly because standard econometric packages were not available, was validated against dummy-variable least squares (coefficients and cluster-robust standard errors on a simulated unbalanced panel; coefficients on the study data); its small-sample correction makes the standard errors slightly conservative. Every reference was checked against publisher or repository records. A separate review of the code, numbers and claims, run with the same model in an independent session, led to corrections of the sample and of several claims. The code is provided as Online Resource 2 and its outputs as Online Resource 1. The author is responsible for the final interpretation and for all claims.

4 Results

4.1 Descriptive patterns

Table 1 describes the sample. Disasters are common and recurrent. Of the 74,856 county-years, 19,027 (25.4%) include at least one major disaster declaration for a natural hazard, and only 78 counties had none between 2000 and 2023. Eighty percent of the county-years with a declaration followed declarations in at least one of the previous five years: 6,514 followed declarations in one of those years, 5,520 in two and 3,182 in three or more, against 3,811 isolated shocks. Federal assistance to households accompanied 37.5% of the shocks, a share that is almost the same for isolated (36.1%) and repeated (37.8%) shocks, so that shock history and assistance vary largely independently. The estimation sample (shock years 2000–2020) contains 16,931 shocks, 38.9% of them assisted.

Table 1
Descriptive statistics

Variable	N	Mean	SD	P10	P90
Outcomes (county-years, 2000–2023)					
Startup rate (firms aged 0 per 100 firms)	72,308	6.486	2.363	3.904	9.426
Establishment entry rate	73,742	9.339	2.955	6.134	12.939
Job creation rate from establishment births	73,742	4.466	3.195	1.861	7.430
Establishment exit rate	73,847	9.189	2.594	6.452	12.147
Net job creation rate	74,856	0.250	6.641	−6.170	6.249
Business applications (log)	59,083	5.286	1.585	3.497	7.477
ERRC constituents (counties, 1995–1999 averages)					
Young-firm base (employment share of firms aged 0–5)	3,119	0.163	0.065	0.099	0.240
Sectoral variety (entropy across 19 sectors)	3,119	2.142	0.329	1.769	2.475
Sectors present (alternative variety measure)	3,119	17.754	1.768	15.800	19.000

Note. Rates are per 100 firms or establishments (percentage points); business applications from 2005. The descriptive sample covers 3,119 counties and 74,856 county-years (2000–2023). 19,027 county-years (25.4%) include a major disaster declaration for a natural hazard; 80.0% of these follow another declaration in the previous five years, and 37.5% include federal assistance to individuals and households. Sources: U.S. Census Bureau (BDS 2023 release; BFS county data); FEMA (OpenFEMA Disaster Declarations Summaries v2)

4.2 Repeated shocks and the erosion of regeneration

Table 2 reports the post-shock changes. After an isolated shock, the establishment entry rate is on average 0.070 percentage points higher over $t + 1$ to $t + 3$ ($p = .006$), and the exit rate does not change. After a repeated shock, entry does not rise and the exit rate is 0.048 points higher ($p = .003$). The difference between repeated and isolated shocks is significant for entry (− 0.079, $p = .001$), job creation from births (− 0.064, $p = .045$) and exit (0.067, $p = .003$), but not for the startup rate (− 0.030, $p = .113$) or the net job creation rate (− 0.125, $p = .083$).

The dose-response estimates in the right part of Table 2 and in Fig. 2 show that the response weakens with repetition and turns significantly negative after shocks preceded by declarations in three or more of the previous five years. For the startup rate, the estimate moves from 0.026 after an isolated shock to − 0.084 after such shocks ($p = .002$); the gap of 0.110 points ($p = .001$) equals 1.7% of the mean startup rate of 6.49. The corresponding gaps are − 0.146 points for establishment entry ($p < .001$), − 0.146 for job creation from births ($p = .004$) and − 0.302 for the net job creation rate ($p = .004$), against a mean of 0.25. Exit is higher after shocks preceded by one or two years with declarations (0.045 and 0.046, both $p = .027$) and similar but not significant after three or more (0.062, $p = .057$). Business applications are not significantly lower after repeated shocks (− 0.4%, $p = .069$). The effects are modest in absolute terms, as expected for county aggregates in which a disaster affects only part of the local economy, but they are consistent across measures of entry, exit and job creation.

Table 2
Post-shock changes by shock history (average of t + 1 to t + 3)

Outcome	Isolated shock	Repeated shock	Difference	0 prior	1 prior	2 prior	3 + prior	3 + minus 0	N
Startup rate	0.015 (0.019)	−0.014 (0.013)	−0.030 (0.019)	0.026 (0.019)	0.007 (0.016)	−0.009 (0.018)	−0.084** (0.027)	−0.110*** (0.032)	60,753
Establishment entry rate	0.070** (0.025)	−0.009 (0.016)	−0.079** (0.025)	0.078** (0.026)	0.004 (0.020)	0.002 (0.022)	−0.069* (0.032)	−0.146*** (0.040)	63,368
Job creation rate from establishment births	0.046 (0.033)	−0.019 (0.020)	−0.064* (0.032)	0.054 (0.033)	−0.008 (0.026)	0.003 (0.028)	−0.092* (0.039)	−0.146** (0.050)	63,368
Establishment exit rate	−0.019 (0.023)	0.048** (0.016)	0.067** (0.022)	−0.021 (0.024)	0.045* (0.020)	0.046* (0.021)	0.062 (0.032)	0.083* (0.038)	63,521
Net job creation rate	0.071 (0.072)	−0.054 (0.043)	−0.125 (0.072)	0.090 (0.073)	−0.026 (0.054)	−0.013 (0.059)	−0.211** (0.080)	−0.302** (0.106)	65,478
Business applications (log)	0.002 (0.004)	−0.004 (0.002)	−0.006 (0.004)	0.002 (0.004)	−0.003 (0.003)	−0.007* (0.003)	−0.004 (0.004)	−0.007 (0.006)	52,648

Note. Coefficients on the shock indicator by condition, from two models per outcome (isolated/repeated; prior years with declarations); standard errors clustered by county in parentheses. "Prior" counts the years with a declaration in t − 5 to t − 1. All models include county and state-by-year fixed effects and indicators for declarations in every other year from t − 5 to t + 3; they do not include interactions with baseline size or capacity. Shock years 2000–2020 (2004–2020 for business applications). * p < .05, ** p < .01, *** p < .001

Repeated shocks occur more often in hazard-prone places, which might explain the weaker response. When we add interactions of the shock with the county's hazard-proneness in 1980–1999 and with baseline size, the pattern holds: the repeated–isolated difference is − 0.068 for entry (p = .007) and 0.054 for exit (p = .017), and the gap between shocks preceded by three or more years with declarations and isolated shocks is − 0.090 for startups (p = .005) and − 0.238 for net job creation (p = .024) (Table 4; Online Resource 1, Table S4b). Hazard-proneness itself is associated with a weaker startup response (− 0.035 per standard deviation, p = .001). In the year-by-year estimates (Online Resource 1, Table S2), none of the pre-shock estimates from t − 3 to t − 1 for the startup, entry, exit and net job creation rates is significant at the 5% level, although a few are close (exit three years before isolated shocks, p = .051; net job creation one year before isolated and repeated shocks, p = .061 and .060). Entry rises mainly in the first year after an isolated shock (0.108, p = .023), while exit rises two and three years after a repeated shock (0.067 and 0.061, p = .026 and .032). The erosion hypothesis is supported for establishment entry and job creation from births, and for startups and net job creation only after shocks preceded by declarations in three or more of the previous five years. The higher exit after repeated shocks is less robust (Section 4.4).

4.3 Recombination capacity and regeneration: exploratory results

The composite ERRC index, estimated first, is positively associated with the startup response after isolated shocks (0.060 per standard deviation, p = .008) but not after repeated shocks (0.014, p = .259), and it is unrelated to the entry response after either (Online Resource 1, Table S6). Its two constituents behave differently (Table 3, panel A). A one standard deviation larger young-firm base is associated with a 0.092-point larger startup response after isolated shocks (p = .002) and with no larger response after repeated shocks (− 0.021, p = .142; difference p = .001). Sectoral variety shows the opposite pattern: it is unrelated to the startup response after isolated shocks (− 0.023, p = .516) and associated with a 0.053-point larger response after repeated shocks (p = .005), although the difference between the two is not significant at the 5% level (0.077, p = .059). For establishment entry, variety is associated with a larger response after repeated shocks (0.055, p = .024; difference p = .017). The isolated-shock coefficients are larger than in Table 2 because the comparison group changes (see the note to Table 3).

When shock history is crossed with federal assistance (Table 3, panel B, and Fig. 3), the young-firm base is most strongly associated with the startup response after isolated, assisted shocks (0.164 per standard deviation, $p < .001$). After repeated, unassisted shocks, the startup rate falls by 0.041 points at average capacity ($p = .013$); the fall is larger where the young-firm base is larger (− 0.062, $p = .001$) and smaller where variety is greater (0.082, $p = .001$). Within repeated shocks, the variety interaction is larger without assistance than with it (difference 0.078, $p = .028$, for startups; 0.134, $p = .007$, for entry), while the young-firm interaction is smaller (− 0.104 and − 0.153, both $p < .001$). After isolated shocks, the variety interaction is also larger without assistance, though not significantly (0.126, $p = .054$), and the young-firm interaction smaller (− 0.114, $p = .034$) (Online Resource 1, Table S3c). The composite index, in a model that pools isolated and repeated shocks, shows the opposite of Exploratory expectation 3: its interaction is positive for assisted shocks (0.041, $p = .010$) and close to zero for unassisted shocks (0.008, $p = .547$).

Table 3
Post-shock changes and the constituents of endogenous resource recombination capacity (ERRC)

A. By shock history	**Startup rate**	**Establishment entry rate**
Isolated shock	0.071** (0.025)	0.118*** (0.032)
Repeated shock	−0.024 (0.014)	−0.020 (0.017)
Isolated × young-firm base	0.092** (0.030)	0.084 (0.046)
Repeated × young-firm base	−0.021 (0.014)	−0.032 (0.019)
Isolated × sectoral variety	−0.023 (0.036)	−0.102 (0.058)
Repeated × sectoral variety	0.053** (0.019)	0.055* (0.024)
Difference, young-firm base (repeated − isolated)	−0.113*** (0.032)	−0.117* (0.052)
Difference, sectoral variety (repeated − isolated)	0.077 (0.041)	0.157* (0.066)
N	60,753	63,368
B. By shock history and federal assistance to households		
Isolated, assisted: shock	0.085* (0.037)	0.146** (0.052)
Isolated, assisted: × young-firm base	0.164*** (0.044)	0.186** (0.063)
Isolated, assisted: × sectoral variety	−0.102 (0.054)	−0.231* (0.094)
Isolated, unassisted: shock	0.061* (0.028)	0.103** (0.036)
Isolated, unassisted: × young-firm base	0.050 (0.036)	0.034 (0.052)
Isolated, unassisted: × sectoral variety	0.024 (0.043)	−0.040 (0.061)
Repeated, assisted: shock	0.002 (0.020)	0.016 (0.025)
Repeated, assisted: × young-firm base	0.042* (0.019)	0.063* (0.026)
Repeated, assisted: × sectoral variety	0.004 (0.028)	−0.033 (0.039)
Repeated, unassisted: shock	−0.041* (0.017)	−0.043* (0.020)
Repeated, unassisted: × young-firm base	−0.062** (0.019)	−0.090*** (0.026)
Repeated, unassisted: × sectoral variety	0.082*** (0.024)	0.101** (0.031)
Contrast, variety: repeated unassisted − repeated assisted	0.078* (0.036)	0.134** (0.050)
Contrast, young-firm base: repeated unassisted − repeated assisted	−0.104*** (0.027)	−0.153*** (0.036)
N	60,753	63,368

Note. Dependent variables are averages over t + 1 to t + 3 (percentage points). Young-firm base and sectoral variety are standardized 1995–1999 measures; interaction coefficients give the change in the post-shock response per standard deviation. Unlike Table 2, these models also interact each shock condition with baseline log employment and include an indicator R for any shock in t − 5 to t − 1, interacted with both constituents and baseline log employment; shock coefficients are therefore evaluated at mean capacity and size and against county-years without recent shocks, which is why the isolated-shock coefficients are larger than in Table 2. All models include indicators for declarations in every other year from t − 5 to t + 3 and county and state-by-year fixed effects; standard errors clustered by county in parentheses. Assisted: at least one declaration in t designated the county for Individual Assistance or the Individuals and Households Program. These analyses are exploratory (Section 3.4). * p < .05, ** p < .01, *** p < .001

Assisted shocks are also more severe. Exits rise most after repeated, assisted shocks (0.084, $p < .001$, without capacity interactions; Online Resource 1, Table S3), and neither constituent moderates exits at the 5% level (Table S3b). Differences between assisted and unassisted shocks may therefore reflect damage as well as support.

4.4 Robustness and limits of the exploratory results

Table 4 summarises the robustness checks for the main estimates (full results in Online Resource 1, Table S4). The weaker entry response after repeated shocks holds with standard errors clustered by state, with repeated shocks defined over three years, with year instead of state-by-year fixed effects, for shock years 2000–2016, with severity controls, with hazard-proneness controls, in percent of the county mean and in long differences. When treated county-years are limited to hurricanes and floods, the estimate is unchanged (− 0.079) but less precise ($p = .071$); in long differences without later shocks, a much smaller sample, it is smaller and not significant (− 0.053, $p = .533$). Other parts of the erosion pattern are less robust (Online Resource 1, Table S4). The higher exit after repeated than after isolated shocks is not significant when treated county-years are limited to hurricanes and floods (0.014, $p = .715$) or in long differences (0.093, $p = .053$; 0.068, $p = .412$ without later shocks), and the rise in entry after isolated shocks is not significant with standard errors clustered by state ($p = .062$), for hurricanes and floods ($p = .052$) or in long differences ($p = .145$).

Table 4
Robustness of the main estimates

Specification	Entry rate: repeated − isolated	Startup rate: isolated × young-firm base	Startup rate: repeated × variety	Startup rate: repeated, unassisted × variety
Baseline (Tables 2 and 3)	−0.079** (0.025)	0.092** (0.030)	0.053** (0.019)	0.082*** (0.024)
Standard errors clustered by state	−0.079* (0.034)	0.092* (0.041)	0.053** (0.018)	0.082*** (0.023)
Repeated = shock in previous three years	−0.054** (0.020)	0.049* (0.024)	0.064** (0.022)	0.108*** (0.031)
Year instead of state-by-year fixed effects	−0.082*** (0.024)	0.120*** (0.031)	0.060** (0.020)	0.088*** (0.025)
Shock years 2000–2016	−0.095*** (0.028)	0.127*** (0.035)	0.056* (0.023)	0.098** (0.030)
Treated county-years limited to hurricanes and floods	−0.079 (0.044)	0.067 (0.040)	0.062* (0.031)	0.057 (0.040)
Severity controls	−0.079** (0.025)	0.092** (0.030)	0.053** (0.019)	0.082*** (0.024)
Scale: shock conditions × baseline outcome rate	—	0.052 (0.039)	0.055** (0.019)	0.080** (0.025)
Scale: outcome as % of county 1995–1999 mean	−0.710** (0.229)	0.420 (0.328)	0.493* (0.242)	0.830** (0.318)
Long difference (outcome minus t − 1)	−0.113* (0.049)	0.070 (0.051)	0.066 (0.036)	0.046 (0.047)
Long difference, no shocks in t + 1 to t + 3	−0.053 (0.085)	0.047 (0.077)	0.069 (0.061)	0.022 (0.072)
Variety = number of sectors present	—	0.086** (0.027)	0.030 (0.024)	0.005 (0.028)
Shock × hazard-proneness (1980–1999) and × size controls	−0.068** (0.025)	—	—	—

Note. Column 1 from the Table 2 model; columns 2 and 3 from the Table 3A model; column 4 from the Table 3B model. In the "% of county mean" row the outcome is the post-shock average expressed as a percentage of the county's 1995–1999 mean, so coefficients are in percent rather than percentage points. "Severity controls" adds shock × hurricane and shock × (two or more declarations in t). The "no shocks in t + 1 to t + 3" row keeps only county-years without later shocks in the post-shock window. — = not applicable (specification unchanged for that column). Standard errors clustered by county (by state in row 2) in parentheses. Full results for startup, entry and exit rates in Online Resource 1, Table S4. * p < .05, ** p < .01, *** p < .001

The young-firm result after isolated shocks is largely a matter of scale. Places with a larger young-firm base have higher startup rates, so a proportional rise after a shock is larger in percentage points. When the shock conditions are also interacted with the county's baseline startup rate, the young-firm interaction falls from 0.092 to 0.052 (p = .183); expressed in percent of the county mean it is 0.42% (p = .200); and in long differences it is 0.070 (p = .165). The larger interaction after isolated, assisted shocks survives long differences but not the scale check (0.076, p = .182), and these shocks are preceded by higher startup rates two years earlier (0.150, p = .012) and by a positive young-firm interaction at that time (0.144, p = .041) (Online Resource 1, Table S5). Exploratory expectation 1 is therefore not supported once scale is taken into account.

The variety result after repeated shocks survives clustering by state, the three-year definition, year fixed effects, shorter samples, severity controls and both scale checks (0.055, p = .004, with baseline-rate interactions; 0.49% of the county mean, p = .042; 0.83%, p = .009, after repeated, unassisted shocks). When treated county-years are limited to hurricanes and floods, it holds for all repeated shocks (0.062, p = .047) but not for repeated, unassisted ones (0.057, p = .151). It is not robust to two

other choices. When variety is measured as the number of sectors present rather than by entropy, the estimates are small and not significant (0.030, p = .200; 0.005, p = .864). In long differences the point estimate for all repeated shocks is similar but imprecise (0.066, p = .067), and the estimate for repeated, unassisted shocks is smaller (0.046, p = .329). Two years before repeated shocks, the variety interaction is negative in all four pre-shock tests (startups − 0.075, p = .070; entry − 0.108, p = .069; for repeated, unassisted shocks − 0.093, p = .060, and − 0.144, p = .045). Part of the post-shock association may therefore reflect a return from below-trend entry in more varied places, which would also explain why it weakens in long differences. For the capacity models by shock history, none of the 24 pre-shock coefficients for startups and entry is significant at the 5% level; for the models crossed with assistance, 7 of 48 are (Online Resource 1, Table S5). The number of tests does not explain the main exploratory estimates. With Benjamini–Hochberg q-values computed over the 24 constituent interactions for startups and entry (and, in parentheses, over all 56 exploratory moderation tests, including the composite index), the variety interaction after repeated, unassisted shocks has q = .004 (.010) for startups and q = .007 (.016) for entry, and the young-firm interaction after isolated shocks has q = .008 (.018) for startups (Online Resource 1, Table S8). These q-values address the number of tests, not the sensitivity to specification and measurement described above. Exploratory expectation 2 thus receives partial support for variety, with the caveats above. Exploratory expectation 3 is not supported overall: only the variety interaction after repeated shocks is consistent with it.

5 Discussion

5.1 Contributions

The special issue asks what sustains entrepreneurship when adversity is continuous and external support fails. Our evidence gives a firm answer to part of this question and a tentative answer to the rest.

First, the study brings the temporal structure of adversity into research on entrepreneurial resilience. Most research treats a crisis as one event and asks how entrepreneurs respond (Doern et al., 2019; Williams et al., 2017). Our results show that the same kind of shock has different consequences depending on what came before. A disaster after a quiet period is followed by a modest rise in establishment entry, consistent with accounts of post-disaster venturing (Shepherd & Williams, 2014; Williams & Shepherd, 2016). Disasters that follow others are followed by more exit and, after declarations in three or more of the previous five years, by less startup activity and net job creation. This erosion is not only a property of risky places, since it holds when the long-run hazard-proneness of counties is controlled for. It is in line with evidence that expected flood risk discourages entry more than single flood events (Jia et al., 2026) and that shocks can leave lasting marks on regional economies (Martin, 2012). For research designs, it implies that pooling isolated and repeated shocks averages a positive and a null entry response, which may help explain why the average effect of disasters on local entrepreneurship often appears small.

Second, the study proposes ERRC as a configuration of agents and raw material and offers initial evidence that its constituents are associated with regeneration under different conditions. A composite index, which we estimated first, suggests that capacity matters only after isolated shocks; the constituents reveal two different patterns. After isolated shocks, places with a larger young-firm base see larger rises in startups, which is in line with evidence that young and small firms limit employment losses after extreme weather (Heinzel et al., 2025), but this association largely disappears once the higher startup rates of these places are taken into account. After repeated shocks, especially without assistance, places with more sectoral variety see smaller declines in startups. This association survives scale and severity checks and the correction for multiple testing, but not all choices of specification and measurement, and part of it may be a return to trend (Section 4.4). Because our measure captures variety across broad and largely unrelated sectors, it is consistent both with the portfolio role that Frenken et al. (2007) attribute to unrelated variety and with the recombination of local resources that ERRC emphasises, the regional counterpart of bricolage (Baker & Nelson, 2005) and resourcefulness (Williams et al., 2021). Separating these interpretations requires measures of related variety and of what entrepreneurs actually recombine.

Third, the study qualifies the expectation that endogenous capacities take the place of failing external support. In a context of permanent crisis, Audretsch and Kariv (2025) find that ecosystem support has no significant direct effect on founders' performance, while community belonging and psychological capital matter. Our evidence on federal assistance to households is mixed. Variety is associated with smaller post-shock declines only after repeated shocks without assistance, which is consistent with substitution, but the young-firm base and the composite index show the opposite pattern, with stronger associations where assistance is present. Because assistance also marks more severe events, we cannot tell whether these patterns reflect support, damage or both. Substitution between endogenous capacity and external support, if it exists, is therefore specific to particular capacities and conditions rather than general.

5.2 Implications for policy

Disaster policy mobilises assistance after each declared event. The erosion result suggests that this logic leaves a cumulative decline in local entry unaddressed in places hit repeatedly, so that support for business formation between events, such as recovery finance and continuity planning, deserves attention alongside emergency aid. If, as Sanders (2022) argues, a more entrepreneurial society is more resilient in a crisis, entrepreneurship policy and disaster-recovery policy in such places should be designed together. The exploratory variety results, if confirmed, would add that economic development strategies in disaster-prone places should weigh the breadth of the local economy, since narrowly specialised places appear to lose more startup activity when shocks recur. These implications rest on associations at the county level and should be tested with designs that can identify the effects of specific policies.

5.3 Limitations and future research

The study has limitations that point to further research. First, ERRC is measured at the county level, while recombination is carried out by entrepreneurs and firms. Our results concern places, not individual entrepreneurs, and they do not show which firms recombine which resources. Firm-level studies in disaster-prone places, using administrative microdata or fieldwork, could observe recombination directly and test whether resourcefulness and psychological capital (Audretsch & Kariv, 2025; Williams et al., 2021) follow the patterns we observe. Second, federal declarations combine the occurrence of a hazard with the decision to declare it (Garrett & Sobel, 2003), and federal assistance to households marks both support and severity. Physical measures of hazard intensity and damage would separate these. Third, county aggregates dilute the effect of disasters that hit only part of a county, which helps explain the modest magnitudes, and the BDS and BFS county data are subject to disclosure protection, including noise in recent BFS releases; Connecticut could not be included. Fourth, the capacity measures are taken before the analysis period and may change over two decades, and the 19-sector variety measure cannot distinguish related from unrelated variety. Finally, the analysis was not pre-registered, the constituent and assistance models were specified after the composite results were known, and they involve many tests. The young-firm results do not survive scale checks, and the variety results depend on the measure of variety, weaken in long differences and may partly reflect a return to trend. They should be treated as hypotheses to be tested in other settings, ideally with pre-specified designs.

6 Conclusion

Entrepreneurship research has asked which resources make entrepreneurs and places resilient to shocks. Our evidence from two decades of disasters in U.S. counties suggests asking also to which shock in a sequence. A disaster after a quiet period is followed by more entry; disasters that keep coming are followed by more exit and, eventually, by fewer startups, also after controlling for counties' long-run exposure to hazards. Which local capacities sustain entrepreneurship under recurrent adversity remains an open question: our exploratory results point to the variety of the local economy rather than to the size of its young-firm base, but they need confirmation. Moving from shock to strength under recurrent adversity is likely to require capacities that are built between shocks, not only support mobilised after them.

Declarations

Author Contribution

C.D.C. conceived the study and the concept of endogenous resource recombination capacity, designed the research, directed the data assembly, the analysis and the drafting of the manuscript, which were carried out with the assistance of a large language model as documented in the Methods section, and reviewed and approved the final manuscript. C.D.C. is the sole author and takes full responsibility for the content.

Data Availability

All data are publicly available from the U.S. Census Bureau (Business Dynamics Statistics, 2023 release, https://www.census.gov/programs-surveys/bds/data.html; Business Formation Statistics, county data, June 2026 release, https://www.census.gov/econ/bfs/data/county.html) and from the Federal Emergency Management Agency (OpenFEMA Disaster Declarations Summaries, version 2, retrieved 29 October 2026, https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2). This product uses the Federal Emergency Management Agency's OpenFEMA API, but is not endorsed by FEMA. The Federal Government or FEMA cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s). The code that builds the panel and reproduces every estimate, table and figure is provided as Online Resource 2, with its outputs in Online Resource 1, and will be deposited in a public repository upon acceptance.

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Figures

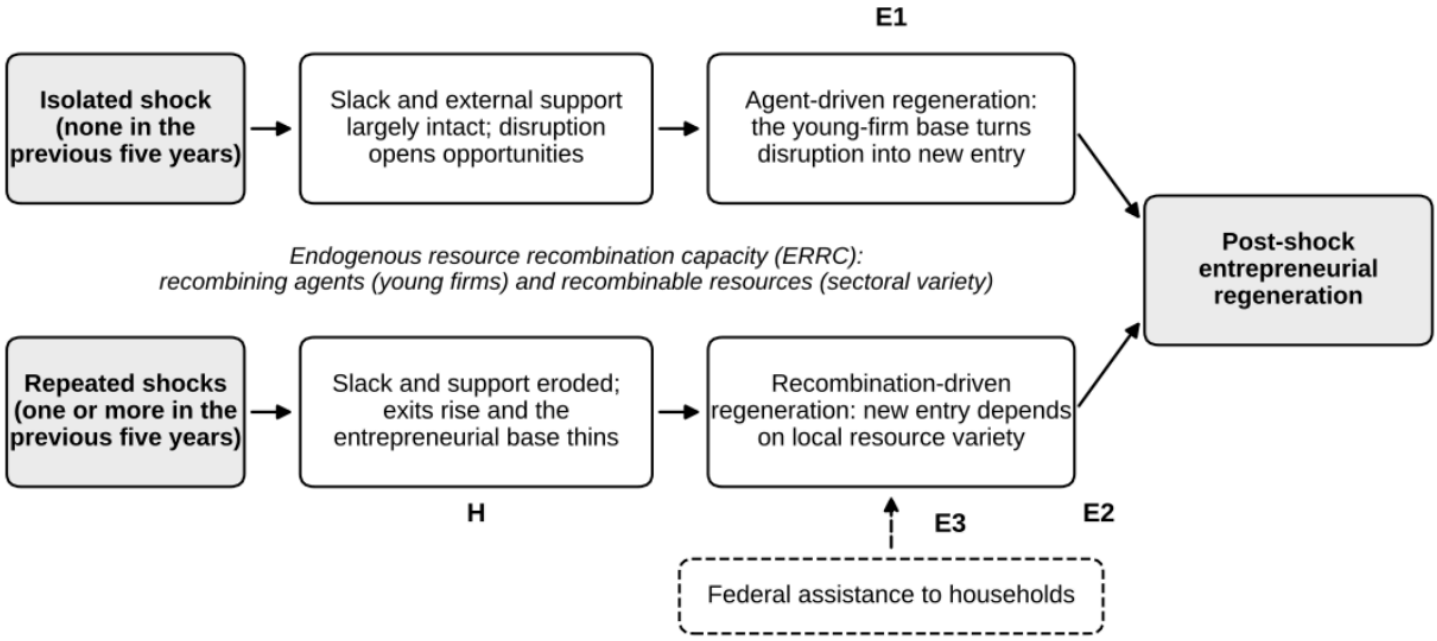

Figure 1

Conceptual framework: isolated and repeated shocks, the constituents of endogenous resource recombination capacity (ERRC) and post-shock entrepreneurial regeneration. H denotes the erosion hypothesis and E1–E3 the exploratory expectations in Section 2.3; the dashed box marks federal assistance to households, which Exploratory expectation 3 expects to weaken the role of ERRC

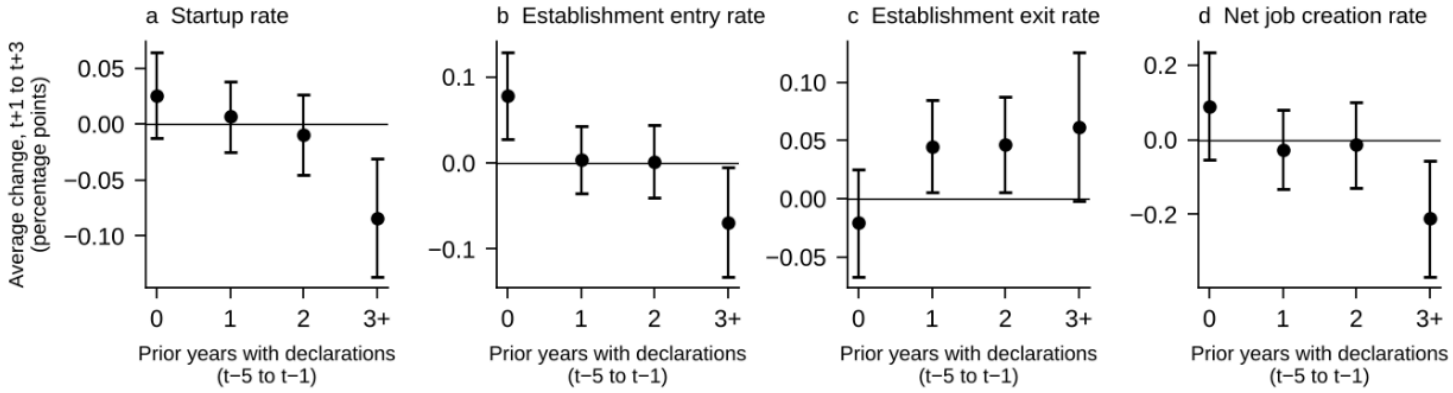

Figure 2

Post-shock changes by the number of prior years with declarations. Coefficients on the shock indicator by the number of years with a major disaster declaration in t−5 to t−1 (Table 2), with 95% confidence intervals; outcomes averaged over t+1 to t+3. Models include county and state-by-year fixed effects and indicators for declarations in every other year from t−5 to t+3; standard errors clustered by county

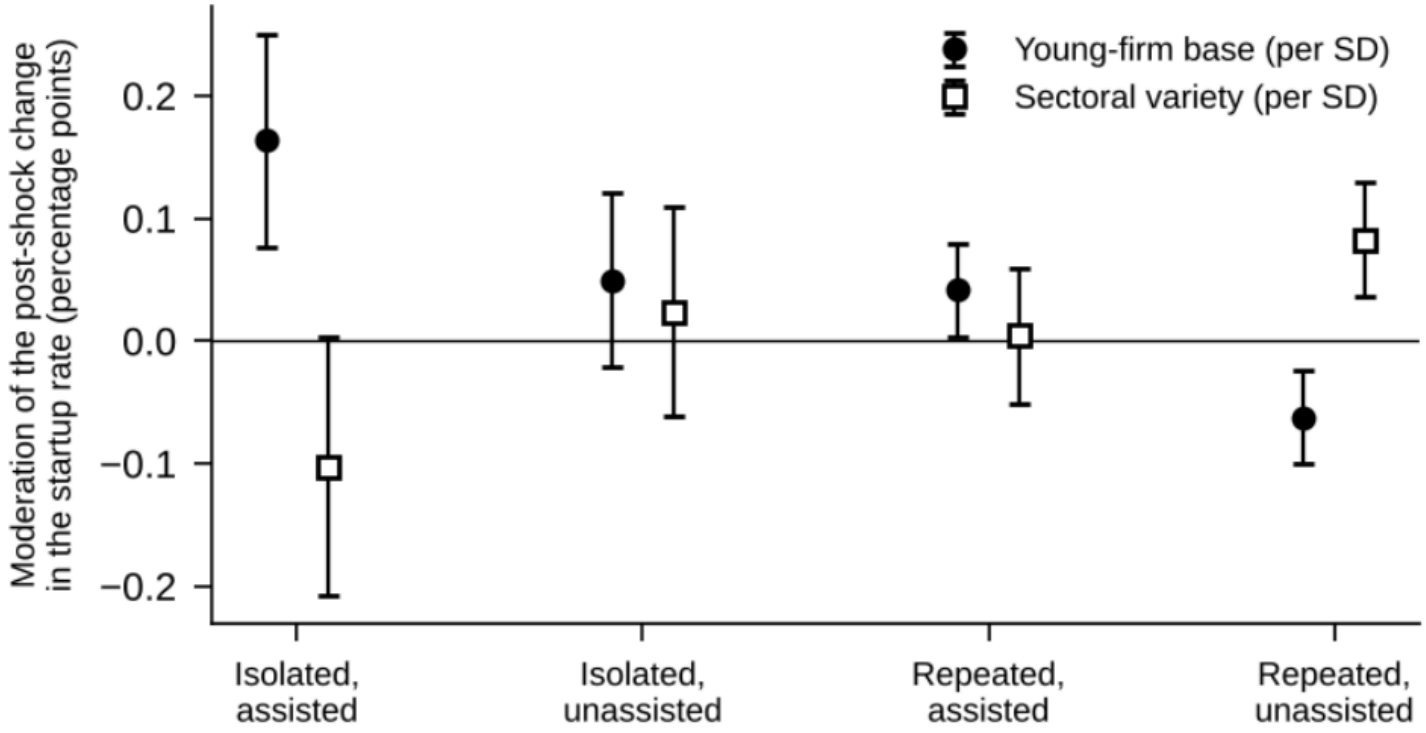

Figure 3

Moderation of the post-shock change in the startup rate by the young-firm base and sectoral variety, by shock history and federal assistance to households. Coefficients per standard deviation with 95% confidence intervals (Table 3, Panel B). Assisted: Individual Assistance or Individuals and Households Program designated for the county

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- 07OnlineResource11.xlsx
- 08OnlineResource2Code.zip