

APPENDIX: SUPPLEMENTARY ANALYSES

§1 Technological Change as an Alternative Outcome

As an alternative manifestation of organizational reconfiguration, we examine whether ventures subsequently expand into technological domains beyond their prior knowledge base using patent data. We restrict the sample to startup-years in which the venture has at least one prior patent application, so that change can be defined relative to its own history; patents are linked to firms using ownership-structure data from ORBIS following Rios (2021). Technological Change is the annual count of patent applications filed in IPC subclass k in year t when the venture had not patented in subclass k in any prior year through $t - 1$. We retrieve patent application data from the EPO PATSTAT database and match patents to VentureXpert/SDC startups. We operationalize technological areas at the IPC-subclass level (e.g., distinguishing H01K “Electric Incandescent Lamps” from H01L “Semiconductor Devices” within the broader H01 class). This level is coarse enough to reflect movement across distinct technological domains rather than incremental refinements within a narrow topic; thus, patenting in a new subclass provides a relatively high-threshold indicator of a change in technological trajectory. Appendix Figure A3 plots the running average of new-subclass filings by years since founding (local polynomial smoothing with 95% confidence intervals), and Appendix Figure A4 shows the distribution of Technological Change (conditional on at least one prior patent).

We estimate Poisson models with fixed effects and robust standard errors (Greene 2004) on the subset of startup-years with at least one prior patent application, since entry into a new subclass is defined relative to the venture's own patenting history. For these models, we also control for the number of subclasses the firm has previously patented in (a breadth measure that complements concentration).

Appendix Table A1 presents analyses examining whether early disaster exposure is associated with subsequent technological reorientation, captured by ventures' entry into new IPC subclasses relative to their prior patenting trajectories. In Model 1, exposure to a local natural disaster in the year post-founding is positively associated with filings in new subclasses ($\beta = 0.144$, $p = 0.002$). Substantively, exposed ventures exhibit an approximately 15.5% higher rate of patenting in new subclasses relative to unexposed ventures. This pattern is consistent with the broader reconfiguration perspective: in addition to compositional differences documented in the LinkedIn subsample, exposed ventures also exhibit greater movement away from their own prior technological trajectories in the patent record.

Model 2 adds county indicators to absorb time-invariant geographic heterogeneity; the association between early disaster exposure and new-subclass filings remains positive and statistically significant ($\beta = 0.110$, $p = 0.019$), though slightly smaller in magnitude. Model 3 shifts the exposure window to shocks occurring in years 2–3 post-founding. The estimated association drops near zero and is not statistically significant. This pattern is consistent with the sensitive-period pattern observed in the survival and IPO analyses: the association between disruption and later reorientation is large when firms encounter the local natural disaster in the immediate post-founding phase.

A key question is whether these differences reflect only short-run disruption responses or persist into later venture ages. Model 4 re-estimates the core specification on the subset of observations where the venture is age 4 or older. The association between early disaster exposure and new-subclass filings remains positive and statistically significant ($\beta = 0.176$, $p = 0.007$). The reorientation pattern is not limited to the immediate aftermath of founding but remains observable well into later venture ages (conditional on being in the patenting risk set). Finally, Model 5 uses an alternative shock measure capturing the local novelty of the disaster type. Exposure to a more locally novel disaster (e.g., an earthquake in a low-seismic region) is associated with even higher subsequent

new-subclass patenting ($\beta = 0.168$, $p = 0.001$). Thus, what also matters is the degree of disruption of expectations and routines beyond categorical exposure to adverse natural hazards. Taken together, these supplementary analyses provide an additional outcome pattern consistent with the possibility of organizational reconfiguration, while remaining conditional on ventures that enter the patenting risk set.

§2 Considering selection into the risk set for patenting in a new class

There is still the question of whether the sample selection for being at risk for patent filings in a new class (which requires having filed at least one patent in any class in the past) might be biasing the results. For that reason, we ran a Heckman (1979) two-step selection model (Models 6 and 7 in Appendix Table A2). Model 6 is the Heckman first-stage model predicting whether a startup has filed for at least one patent in the past.¹ We calculated a variable counting the number of active startups in a focal startup's narrow technological area as classified by VentureXpert/SDCPlatinum² that have filed for a patent in the past year, as a marker of heterogeneity in patenting among startups in an industry. Startups in technological areas that are more patenting-intensive are likely to patent more owing to either IP protection needs or norms in that technology area. Yet being in a more patent-intensive area doesn't directly influence patenting in new classes apart from driving selection into the risk set from having a patent at all.

¹ The controls for patent portfolio composition (number, classes, and concentration) are not added in this equation since they are a consequence rather than an antecedent of having filed for a patent in the past.

² For example biotech has multiple such narrow technological areas (46), such as Agricultural/Animal Biotechnology, Biochemical Products, Biosensors for Industrial Applications, Biosensors for Medical Diagnostic Applications, Biotech Processes for Enhanced Oil Recovery/Mining, Biotech Processes for Food Industrial Applications, Biotech Processes for Pollution/Toxic Waste Control, Biotech Related Analytical Instruments & Apparatus, Biotech Related Animal Health & Nutrition Products, Biotech Related Commodity Chemicals, Biotech Related Fine Chemicals (NOT Pharmaceuticals), Biotech Related Food Diagnostics, Biotech Related Food Enzymes and Cultures, Biotech Related Production Equipment, Biotech Related Research & Other Services, Biotech laser and optronic applications, Biotechnology in Pharmacology, DNA/RNA Probes, Microorganisms to raise plant yield, Genetically Engineered Animals, Genetically Engineered Plants, Human Biotechnology, Immune Response Effectors (interferons, vaccines), In Vitro Monoclonal Antibody Diagnostics, and so on.

We use this variable as an instrument in the first-stage equation predicting whether a focal startup has filed at least one prior patent. The coefficient on this variable is positive and statistically significant, suggesting that patenting prevalence within the startup's narrow industrial sector is associated with the focal firm's likelihood of having patented. The coefficient on disaster exposure is negative, indicating a slightly lower probability of having a prior patent in the first stage.

Model 7 in Appendix Table A2 reports the second stage of the Heckman model. In this model, the association with the shock remains positive and statistically significant among selected firms and is only slightly smaller in magnitude. Thus, the positive association between early disaster exposure and new-class patenting remains after accounting for selection into the patenting risk set.

In Model 8, we tested for a discrete version (Probit) of the second stage DV (whether the startup in a particular year filed any patents in a new high-level 4-digit EPO class) to test whether, beyond the main effect, the findings are robust to considering the discrete act of change to one or more new classes. Model 8 is a Heckman Probit (HeckProbit) model since the second stage is now a discrete DV. The results are similar using this alternative 'extensive margin' or discrete conception of technological change, even after considering selection into the set of firms that have at least one prior patent.

§3 Alternative specification for technological change

As noted previously, we are unable to use startup fixed effects because the shock indicator is time invariant within startups. A random-effects specification is estimable, although the random intercept may be correlated with the focal independent variable. We nonetheless estimate a random-effects QMLE Poisson model with startup-clustered standard errors, reported as Model 9 in Appendix Table A3. The coefficient on early disaster exposure remains positive, is statistically significant at $p < 0.05$, and is similar in magnitude to the main estimate. Thus, the positive

association between early disaster exposure and subsequent technological change is also present in this alternative specification.

§4 Alternative Measure of Technological Change: Mahalanobis Distance

We assess robustness using an alternative measure of technological change: Mahalanobis distance (Bloom et al. 2013). Because Mahalanobis distance is positively skewed—startups are more likely to patent near their prior knowledge domains than far from them—we use its logarithm as the dependent variable in the second stage of the Heckman model. This specification is reported as Model 10 in Appendix Table A3. The coefficient on early disaster exposure is positive and statistically significant, indicating that the association is robust to a continuous, distance-based measure of technological reorientation.

§5 IPO Analyses in Samples with Greater Baseline IPO Plausibility and Predicted IPO Propensity

Appendix Table A4 reports four restricted-sample analyses. Models 13, 14, and 16 use baseline indicators of greater IPO plausibility; Model 15 provides a broader propensity-based sensitivity using the full covariate set. Model 13 restricts the sample to consumer-facing ventures (B2C or ventures targeting multiple segments including consumers), which may be more readily evaluated by generalist public investors than B2B or B2Gov ventures.

Model 14 estimates IPO propensity from static characteristics—industry and target-customer segment—and re-estimates the main IPO specification among ventures in the top quartile of predicted propensity. This is the cleanest *ex ante* propensity restriction.

Model 15 estimates IPO propensity using the full covariate set, including dynamic characteristics, and re-estimates the main specification among ventures in the top quartile. Because

this broader sensitivity uses time-varying covariates, we do not treat it as a strictly ex ante definition.

Model 16 restricts the sample to Computer Science and Engineering ventures, a sectoral group commonly viewed as containing plausible IPO candidates, while recognizing that many such ventures compete for public capital.

Across the three baseline-plausibility restrictions and the broader full-covariate sensitivity, the main pattern persists: early disaster exposure is not associated with a uniformly higher IPO hazard, but the disaster $\times$ market-hotness interaction remains positive and statistically significant. The interaction estimates in Models 13 and 14 are larger than in the full-sample model; those in Models 15 and 16 are similar or somewhat smaller. These results indicate that the main IPO pattern is not confined to ventures with low baseline plausibility of going public.

§6 Alternative Measures of the Disaster

Novelty. Although natural disasters are difficult to predict at any moment, events vary in novelty relative to a location's prior experience. More locally novel disasters may be more disruptive because affected organizations are less likely to have established routines for them. For example, a place that regularly experiences wildfires but not floods may be prepared for wildfire disruption yet poorly prepared for flooding and related landslides (Starr 2006: 61–66). Under the proposed account, more locally novel shocks may impose greater early adaptive demands and be associated with stronger long-run differences in responsiveness.

We consider the novelty of disaster shocks based on location and history. We calculate shock novelty as the conditional probability that a disaster occurring in the year post-founding is of a locally uncommon type. We use a rolling 30-year history of disaster types in the focal county to establish local priors, rather than an unbounded window, both because collective memory is finite and because comprehensive FEMA data begin in 1953, 32 years before our study sample. We define

the conditional probability as $P[D(k,Y,C) \mid D(Y,C)] = P[D(k,Y,C)] / P[D(Y,C)]$.

Here, $D(k,Y,C)$ denotes a disaster of type k in year Y in county C , and $D(Y,C)$ denotes any disaster in year Y in county C . A high conditional probability indicates a locally common shock, whereas a low value indicates a less familiar shock that may impose more complex adaptive demands. The numerator is the average annual incidence of a disaster of type k in county C during years $Y-30$ through $Y-1$; the denominator is the average annual incidence of any disaster in that county over the same period. The resulting measure lies in the interval $(0,1)$. We code “Encountered more novel local natural disaster in year post founding” as 1 when the conditional probability of the observed disaster type is below the sample mean.³

In Model 20 of Appendix Table A6, we replicate the main IPO-hazard model after replacing the first-year disaster indicator with an indicator for a more locally novel disaster. The main effect of encountering a more novel disaster is not statistically significant. The interaction between novel-disaster exposure and market hotness is positive and statistically significant and is larger than the main-model interaction (cf. Model 10, Table 5). The larger interaction for more locally novel shocks is consistent with the proposed account that less familiar disruptions may impose greater adaptive demands; it does not by itself identify a mechanism.

Damage. We next measure the shock in terms of damage per capita. The degree of damage from a disaster is often related to features of the local area such as population density, kinds and age of construction, and level of economic development, so a large part of the damage is a function of relatively fixed characteristics of a county which get absorbed by the county indicators in the model. Even so, damage data for individual disasters are hard to ascertain exactly, but a good proxy is the

³ We did not use the raw continuous measure since that is very correlated with there being a disaster event at all. Note that this measure of novelty captures systematic novelty based on prior experience of disaster in the county. However, there is residual novelty in the impact or path of disasters which is largely random. For example, during the 1989 Loma Prieta earthquake in Northern California, the greatest property damage did not occur in the lower-income parts of the city such as the mission district, as might have been expected due to the older buildings there, but in the affluent Marina district where broken gas lines led to cascading fires that engulfed structures on the coast (USGS 1998; NBC 2022).

total dollar value of applications for federal aid (but not necessarily granted) to recover from the disaster that was filed with FEMA in the county of the focal startup (FEMA 2024). We then normalized this damage measure by dividing it by the number of individuals in the county who were affected by the disaster and needed assistance. In Model 21 of Appendix Table A7, we replaced the main disaster shock dummy with the log of per-capita damage in the focal startup's county and added its interaction with market hotness. The interaction coefficient is positive and statistically significant, suggesting that the proposed effects are robust to considering local damage from the disaster the focal startup encountered in the year post-founding as an alternative measure of the shock.

Next, we refine the damage measure to focus on infrastructure. As the examples in the manuscript suggest, power outages, disrupted roads and rail, and failures of communications infrastructure can interfere directly with normal operations. We therefore calculate log per capita infrastructure damage using the dollar value of applications for FEMA public-assistance categories C through G (again, applications rather than amounts granted). In Model 22 of Appendix Table A7, we replace the main disaster indicator with this measure and interact it with market hotness. The interaction is larger and statistically significant, a pattern consistent with the possibility that infrastructure disruption alters operating demands in ways relevant to later responsiveness.

§7 Robustness Checks: Alternative Hazard-Model Specifications

The reasons for using a Weibull hazard specification are discussed in the main manuscript's Data and Methods section. For robustness, Model 23 in Appendix Table A8 estimates a conditional logit model of IPO as a discrete event over time, with county fixed effects and standard errors clustered by county. The coefficient on the interaction between disaster exposure and market hotness remains positive and statistically significant. Magnitudes are not directly comparable with

those from the Weibull model because the conditional logit assumes a fixed event baseline within county, rather than incorporating county indicators into the Weibull scale parameter in the same functional form as other covariates.

Since our shock is cross-sectional—startups either encounter disaster in the year post-founding or not—we are unable to add fixed effects on startups. One possibility is running a random-effects logit (QMLE) model with random effects on startup; while this model is estimable, it is not necessarily well-founded since the focal independent variable does not vary over time. Hence, the RHS variables are likely correlated with the random effects, violating the assumptions about using random effects. Nonetheless, we ran the aforementioned model, shown as Model 24 in Appendix Table A8. The interaction remains positive and statistically significant in this model as well.

We also tested for the robustness of the findings to other common hazard specifications. Model 25 in Appendix Table A8 is a piecewise exponential model estimated with Jesper Sorensen's STPIECE routine in Stata, which allows for different parts ('pieces') of the organization's life to have different discrete baseline hazards. For this model, we took the 'pieces' to be three years wide: 1st to 3rd year, 4th to 6th year, and so on. The coefficient on the interaction between shocked firms and industry hotness is positive and statistically significant in this alternative specification as well. In Model 26 of Appendix Table A8, we use the Cox proportional hazards specification and find similar patterns for the main findings. In the Cox specification, we also added the interaction term in the duration dependence (TVC) parameter when estimating the semiparametric proportional hazard. The duration-dependence estimate is negative, consistent with attenuation over time, but is not statistically significant in this model.

§8 Internal Differences Between Shocked and Unshocked Startups

Our conceptual framework suggests that the adaptation demands imposed by a natural disaster during the year post-founding may be associated with persistent organizational differences relevant to later change. We do not observe the specific routines that would generate such persistence directly, but we can examine whether shocked and unshocked organizations differ in attributes related to slack and flexibility. Prior work notes that external shocks can create resource and coordination demands that overwhelm normal organizational arrangements (Comfort 1985; Weick 1993) and make redundancy and slack especially salient (Thompson and Hawkes 1962; Reilly 2022). If such priorities persist, they may appear in liquidity reserves and in the balance between flexibility and efficient asset use. We therefore examine current ratios, cash ratios, and current-asset turnover as descriptive indicators of that tradeoff.

To measure this particular aspect of the relative emphasis on slack/flexibility versus efficiency/tight coupling, we gathered financial data on the startups using the ORBIS database, which includes some private company data. However, we were only able to match a small fraction of the startups to detailed balance sheets, P&L, and employee counts, and even the matched data had gaps in the panel, so the following analysis involves aggregate comparisons to help triangulate the long-run persistence of certain features. Below, we discuss comparisons in various slack vs. efficiency ratios among shocked and unshocked startups, which are also shown in Appendix Table A9 of this appendix.

First, we compared the average current ratio of shocked and unshocked firms. The current ratio is the ratio of current assets to current liabilities and is often used as a measure of liquidity for the business. Startups, in general, operate with high current ratios since their assets are often funded by equity rather than short-term loans. We find that shocked firms have an average current ratio of 3.8 (SD 5.7) versus 3.3 (SD 4.4) for unshocked firms. This difference in average liquidity is also statistically significant ($t = 3.93$, $N = 7,104$), suggesting that shocked firms, consistent with an

emphasis on flexibility, retain greater liquidity on average.

Next, we considered the cash ratio, which is a more restrictive or conservative measure of liquidity and is calculated as the ratio of cash and cash equivalents to current liabilities. While venture-funded startups, in general, have higher cash ratios due to less reliance on short-term debt, shocked startups have substantially higher cash ratios on average (2.35 with SD 4.8) compared to unshocked startups (1.9 with SD 3.5). The difference of 0.47 is statistically significant ($t = 4.52$).

Apart from slack or flexibility evident in liquidity and cash holdings, the other side of the coin is efficiency ratios, which attempt to calculate the utilization of assets relative to the revenue generated. We calculated current asset turnover as a ratio of operating revenue to current assets. This measure captures how efficiently a firm uses its more liquid assets to generate revenue. We find that shocked startups have lower current asset turnover (1.7, SD 3.3) compared to unshocked startups (2.6, SD 6.7), and the difference is statistically significant ($t = -5.79$). Thus, shocked startups are, on average, less efficient and retain more slack in their use of available liquidity compared to unshocked startups.

A possible consequence of the greater emphasis on slack and strategic flexibility among shocked organizations is an enhanced capacity for subsequent strategic change (Bentley and Kehoe 2020), experimentation (Bradley et al. 2011), and coordination and innovative effort, albeit with greater variability (Agrawal et al. 2018).

§9 GSEM models of multiple outcomes

While we consider various dependent variables to illustrate the change propensities of shocked versus unshocked startups, we next use simultaneous equations in a GSEM framework. GSEM models allow the estimation of multiple different kinds of dependent variables, including non-overlapping samples. However, the estimation of GSEM models relies on somewhat strong assumptions about joint distributions, which are sometimes not met in data analyses. Nonetheless, in

Appendix Table A10, we show the results of GSEM estimation for variables failure, IPO, patenting in new high-level classes, buyout, and technological change measured in Mahalanobis distance. These models do not include county indicators since simultaneous estimation in GSEM is computationally intensive and, in our case, does not converge with county fixed effects. To summarize, we find that even in these models, the main empirical patterns remain similar.

§10 Considering disasters and technological change as a continuum.

We next compared the responses of shocked firms to encountering future disasters, as opposed to technological change. These comparisons are illustrative because encountering, for example, a similar type of disaster as the one encountered in the year post-founding (e.g., earthquake in the first-year post-founding, and then earthquake again in some period t for the startup) is rare. Second, what counts as ‘handling’ future disasters is somewhat subjective, so we use failure as an inverse measure of handling a disaster well. Finally, for both of the above reasons, we use simple comparisons of annualized failure rates (i.e., if the startup-year following the repeat disaster has a failure event for that startup). We used FEMA data on types and dates of major natural disasters for our analysis, using the same FEMA data described in the main manuscript. We find that shocked startups that encountered a similar type of natural disaster have lower average annual failure chances in the following year (1.79% per year) than shocked startups that encountered a different type of natural disaster (2.42% per year).

The comparison of these ongoing external environmental changes with the consequences of internally driven change is not straightforward. The experience of additional disasters of a ‘same type’ or a ‘different type’ is applicable for all shocked firms, but entry into new patent classes can only be observed for firms with at least one prior patent. However, startups with prior patents have much lower failure rates, and are older, on average, potentially due to various benefits accruing to

patenting startups (e.g., Ménière et al. 2023). With this constraint, once we adjust for the lower failure rates of startup-years with at least one prior patent, the failure rate of shocked startups the year after filing a patent in a new high-level 4-digit class is on average 3.9% per year.

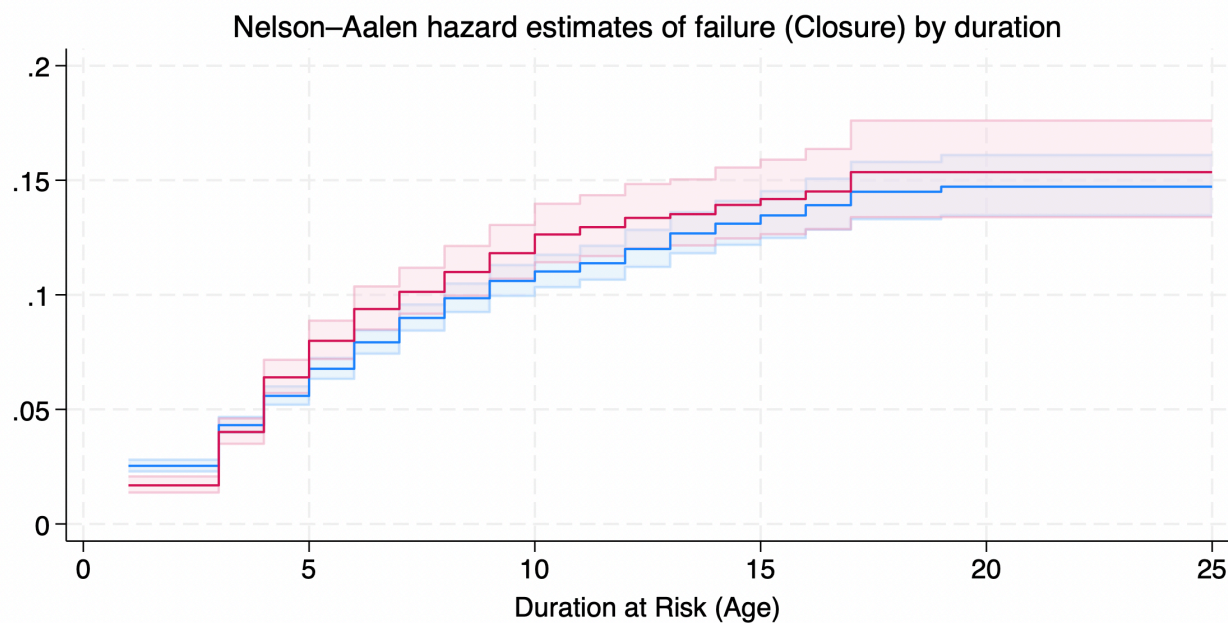
These descriptive comparisons suggest possible variation in how organizational differences associated with early shock exposure carry over to later change settings. Because the comparisons involve different events, samples, and outcome definitions, they should be treated as illustrative rather than as evidence of a common redeployable capability.

Appendix References

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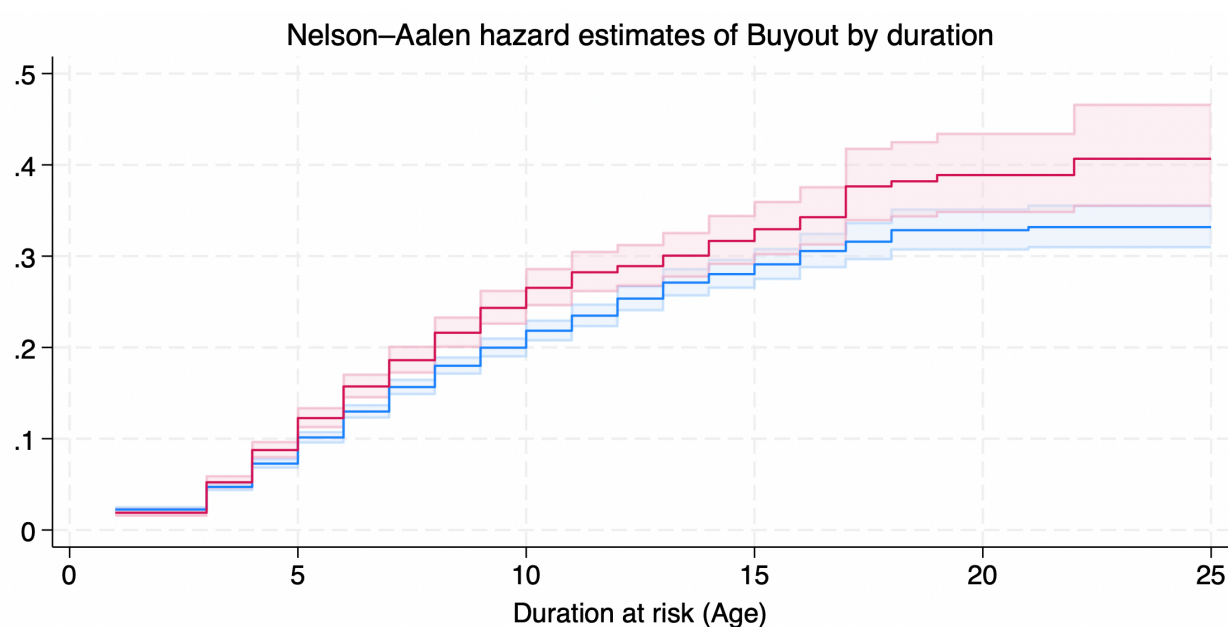
APPENDIX FIGURES

Appendix Figure A1: Nelson–Aalen cumulative-hazard estimates of failure (closure) by venture age for shocked and unshocked startups.

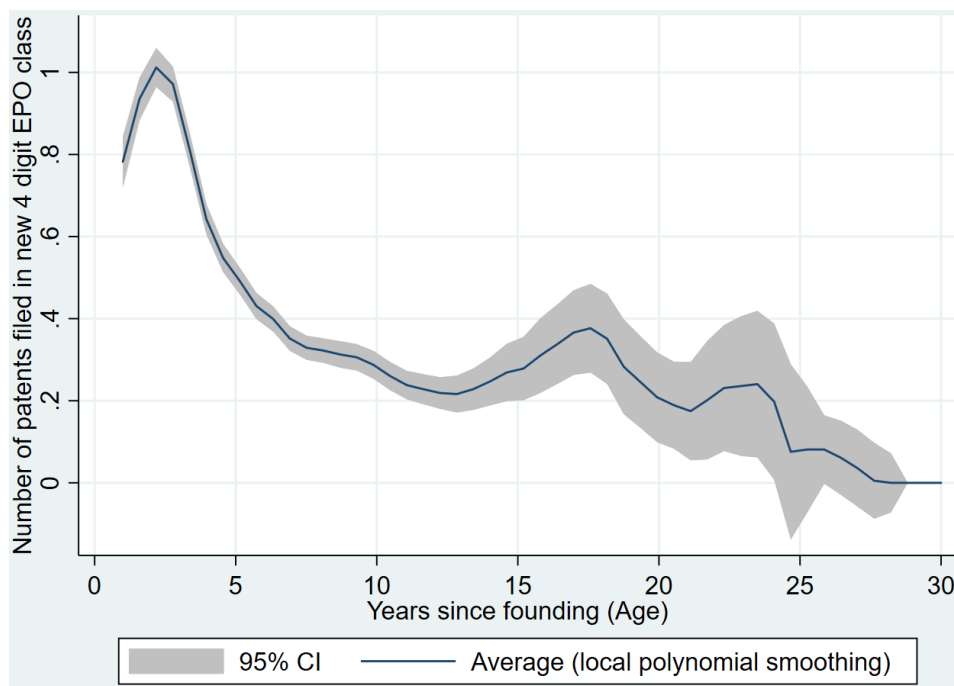


Notes: Venture age is truncated at 25 because terminal outcomes are sparse beyond that point. Shaded areas show 95% confidence intervals. These nonparametric cumulative-hazard estimates are descriptive and do not account for observed heterogeneity captured in the regression models.

Appendix Figure A2: Nelson–Aalen cumulative-hazard estimates of buyout by venture age for shocked and unshocked startups.

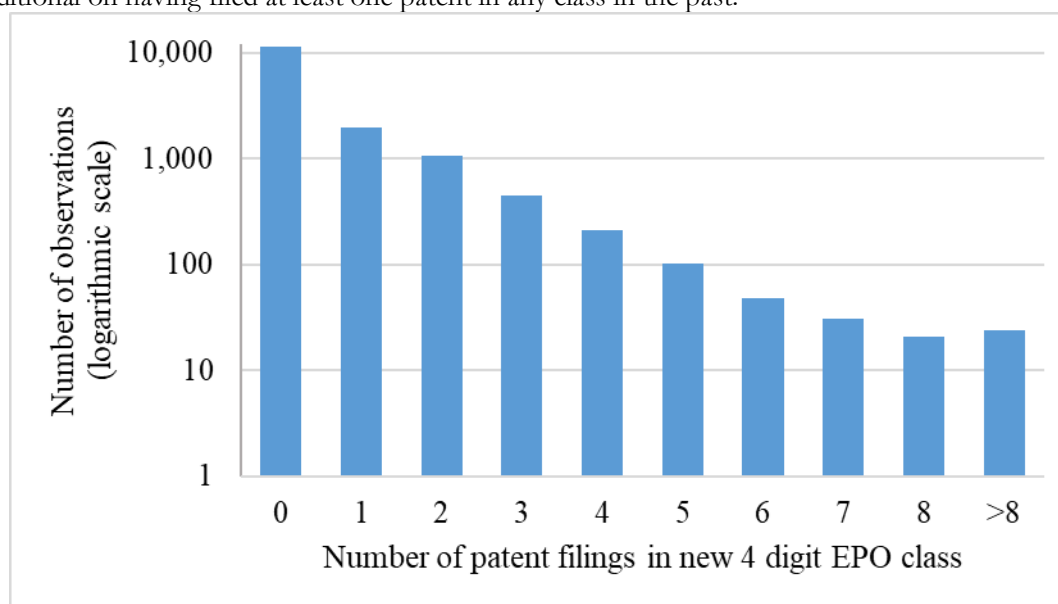


Appendix Figure A3: Patent filings in new classes by years since founding, local-polynomial smoothed average, conditional on having filed at least one patent in any class in the past.



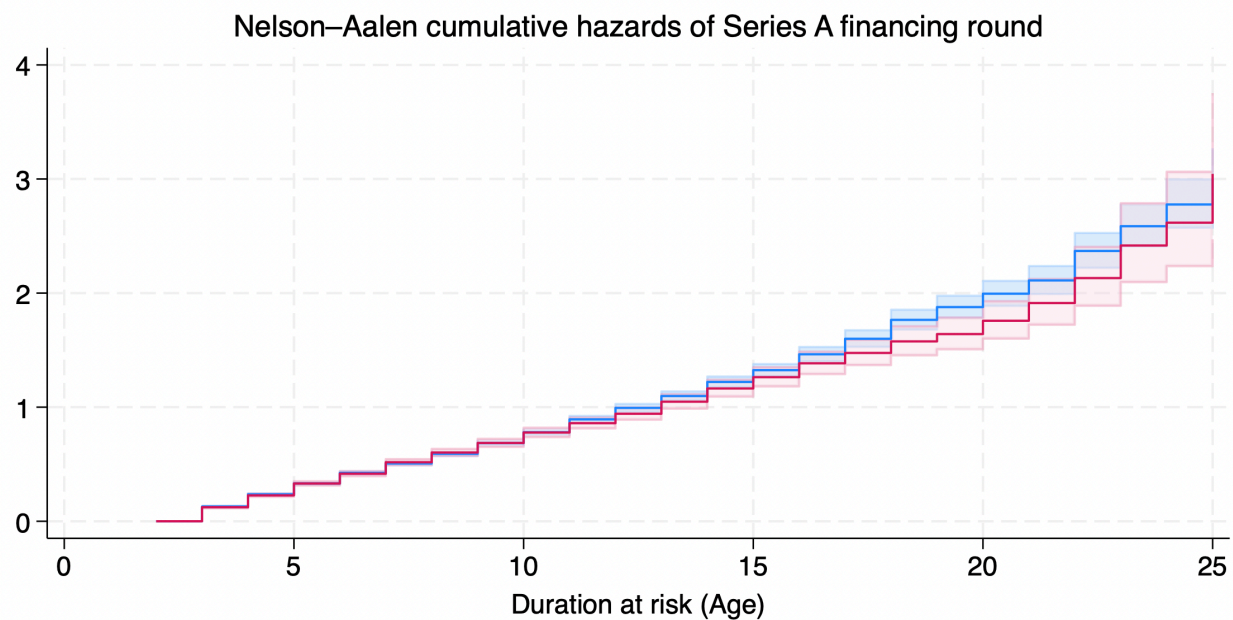
Appendix Figure A4: Distribution of new-class patent filings

Conditional on having filed at least one patent in any class in the past.

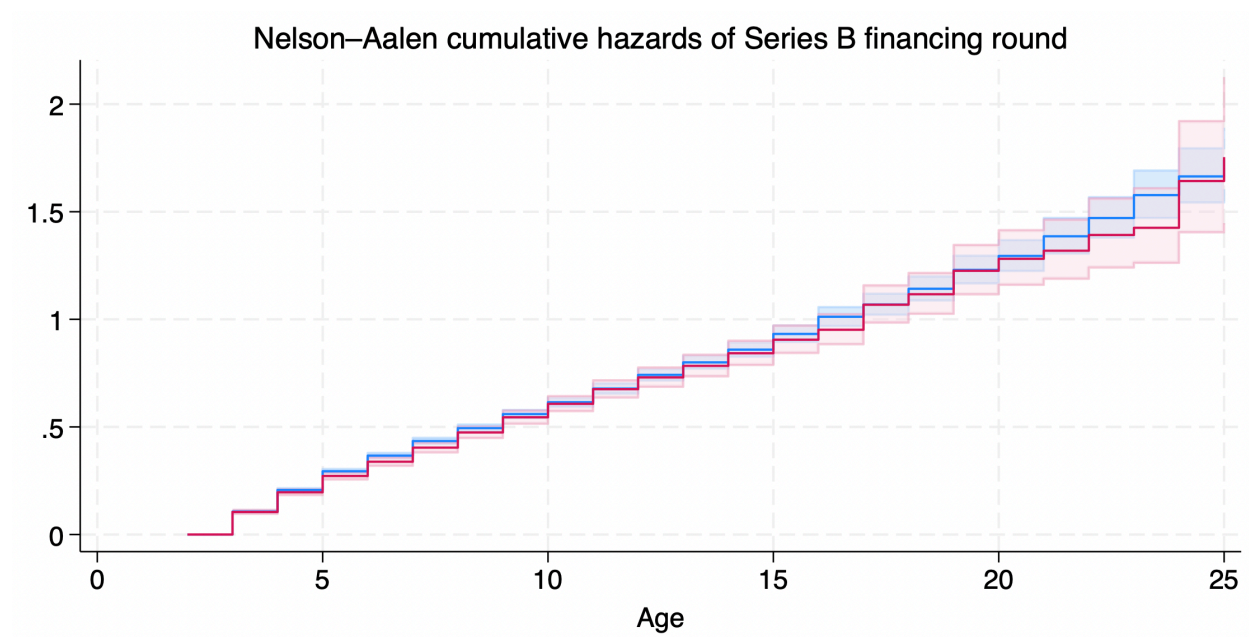


Note: Y axis is on logarithmic scale for readability, but y axis markings are of absolute frequencies. Last category (>8) is the total for the right tail.

Appendix Figure A5: Nelson–Aalen cumulative-hazard estimates of Series A financing by venture age for shocked and unshocked startups, with 95% confidence intervals.

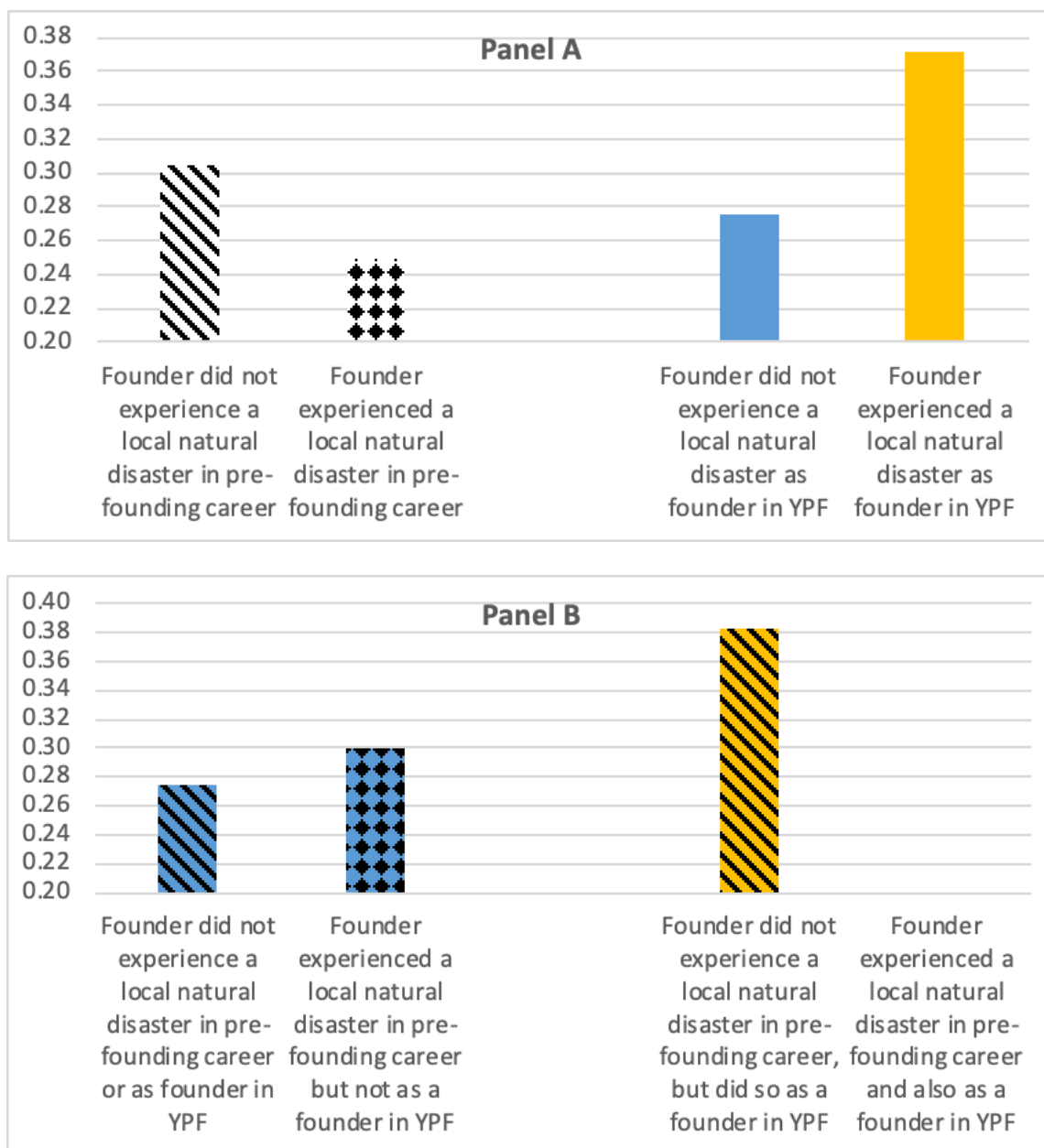


Appendix Figure A6: Nelson–Aalen cumulative-hazard estimates of Series B financing by venture age for shocked and unshocked startups.



Appendix Figure A7: Founders' prior disaster experience and IPO chances

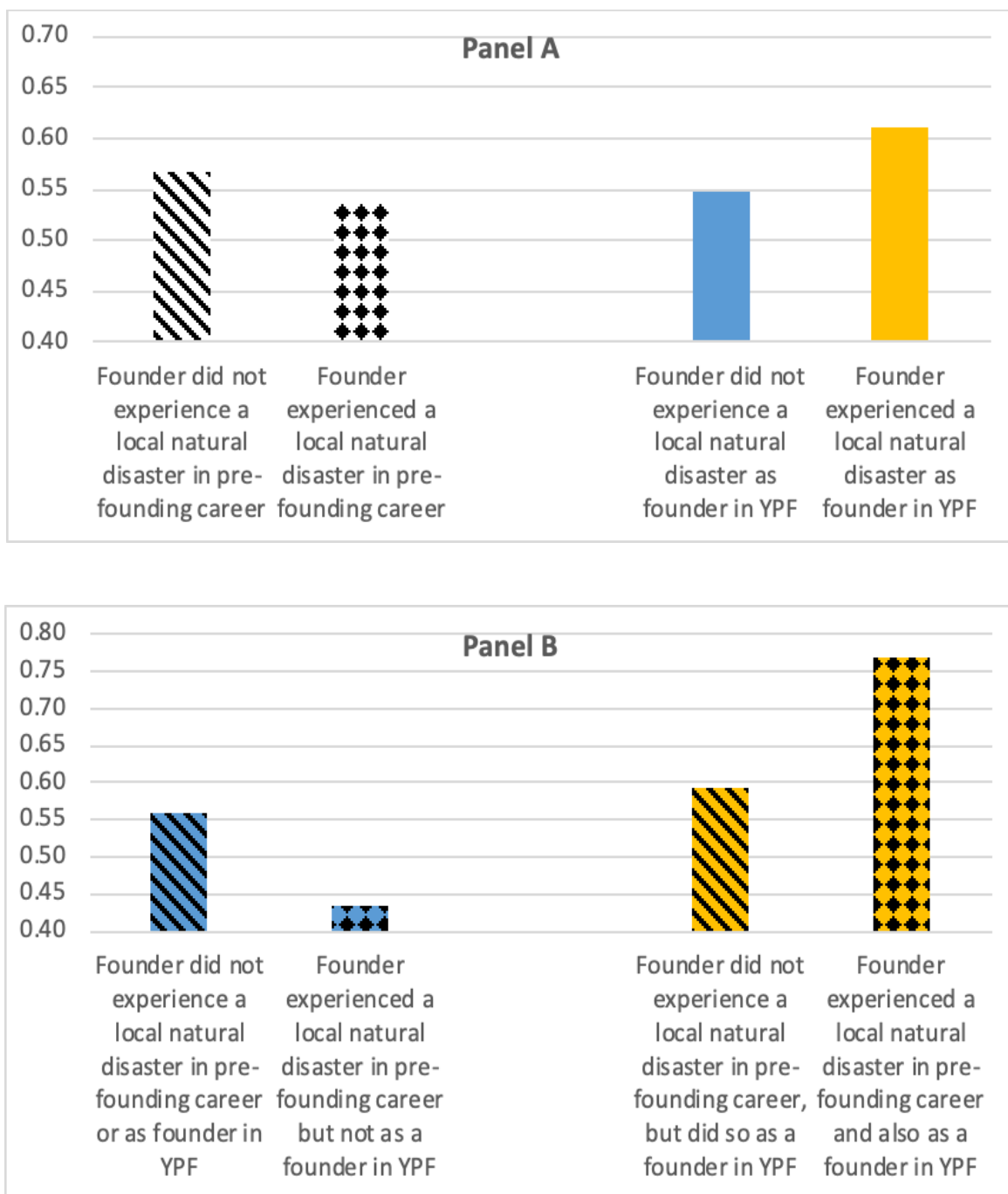
Y-axis is the fraction of startups that IPO'd: Comparison of founders' pre-career experience with a local natural disaster (or not), vs encountering a local natural disaster as a founder in the year post founding (or not). **Panel A** shows separate means for comparison, and **Panel B** shows the crossed means across the two categories as described in the bar labels.



Note: $N = 315$ founder observations from biotech startups with founder LinkedIn profiles. The sample is likely success-biased; comparisons are illustrative. Fewer than 1% were exposed both before founding and in the founding year, and none IPO'd, so the final Panel B bar is zero.

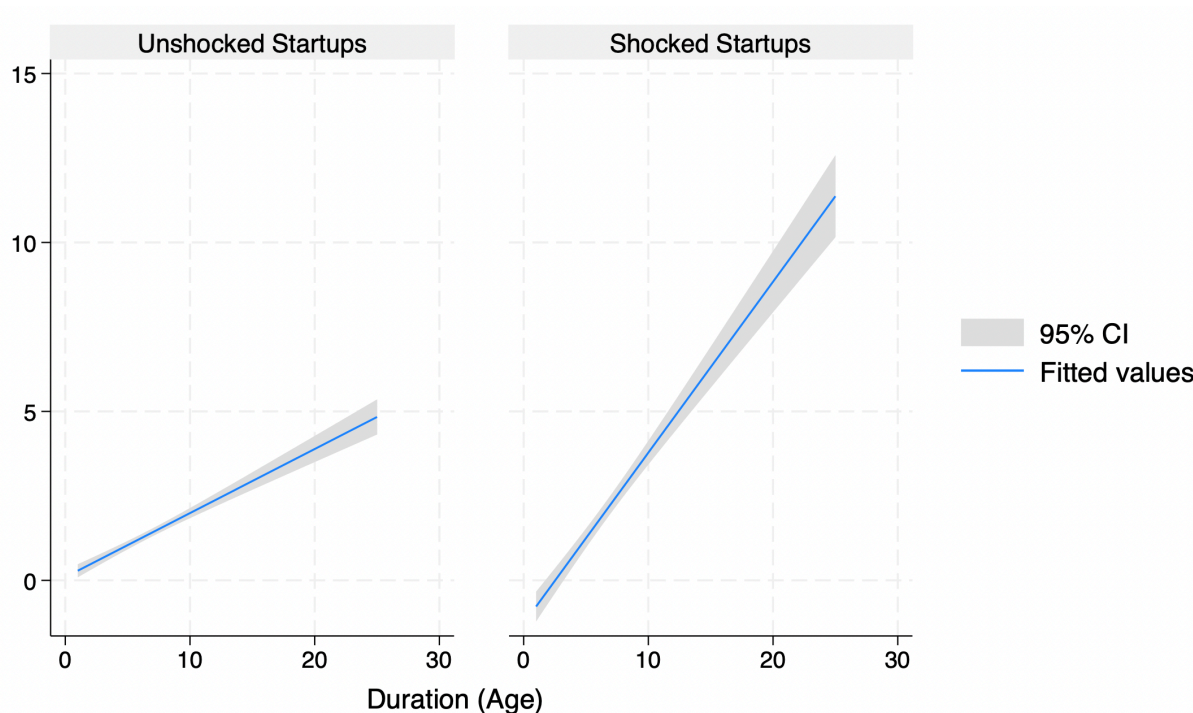
Appendix Figure A8: Founders' prior disaster experience and technological change

The Y axis is the average number of patents filed in new 4-digit classes in a year among startups with at least one prior patent: Comparison of founders' pre-career experience with a local natural disaster, vs encountering a local natural disaster as a founder in the year post founding. **Panel A** shows separate means for comparison, and **Panel B** shows the crossed means across the two categories.



Note: Comparisons are illustrative due to the small sample

Appendix Figure A9: Differences between unshocked (left) and shocked (right) startups in the number of employees per startup with descriptions of adaptive language in their LinkedIn profile/resume (y-axis) versus duration (i.e., startup age) on the x-axis (age truncated at 25 due to sparse data beyond that)

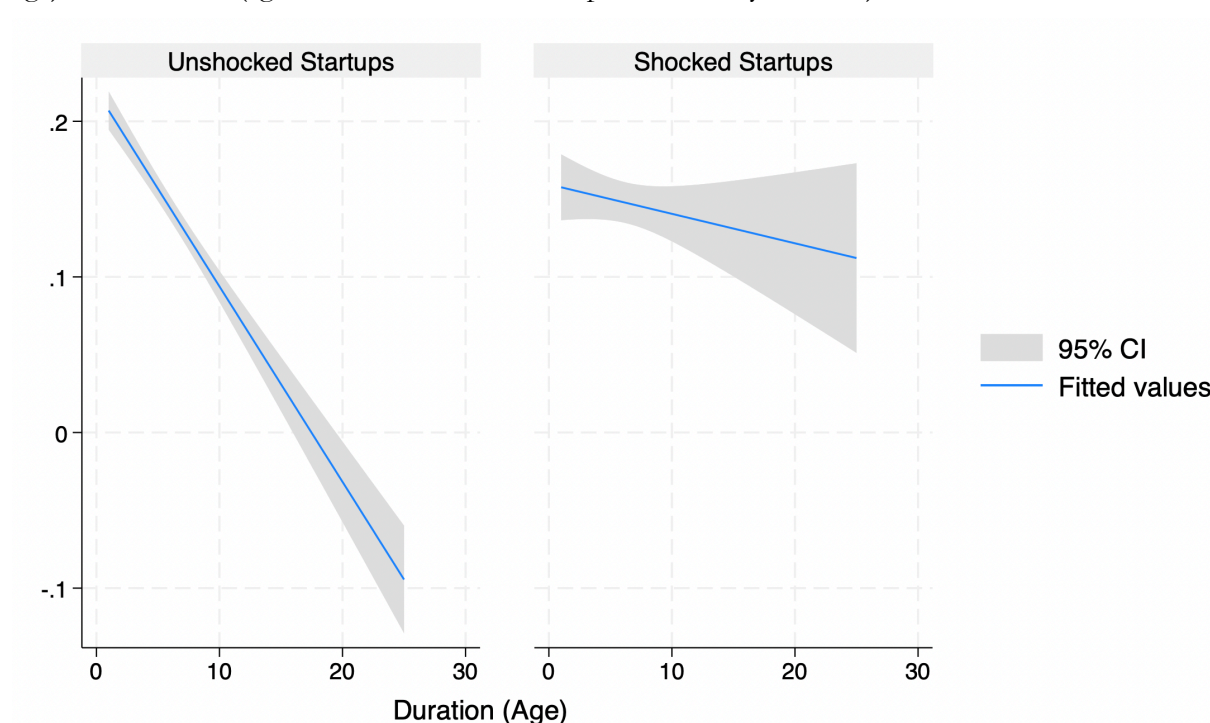


Notes common to Appendix Figures A9-A12:

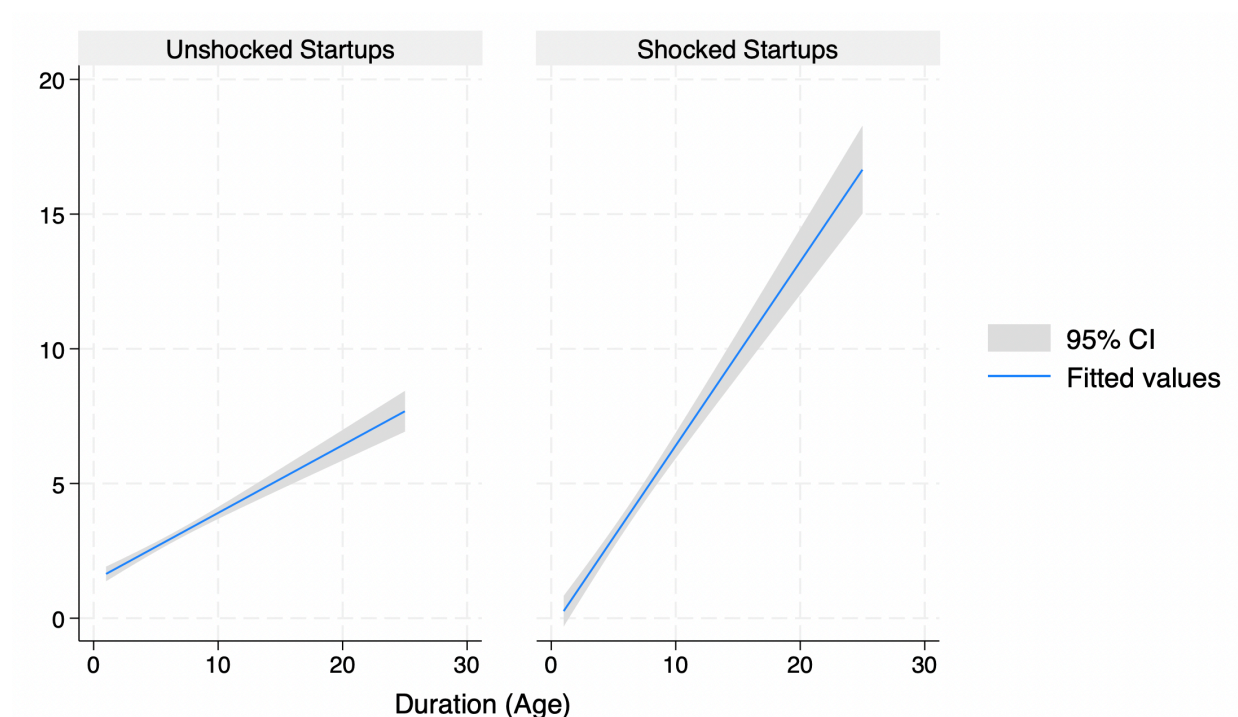
* These figures correspond to Figures 4–7 in the main text but show the longer time period.

* Note that while the linear fit and CIs might cross over sometimes to below zero, that is an artifact of the fits and CI rather than a negative number of employees.

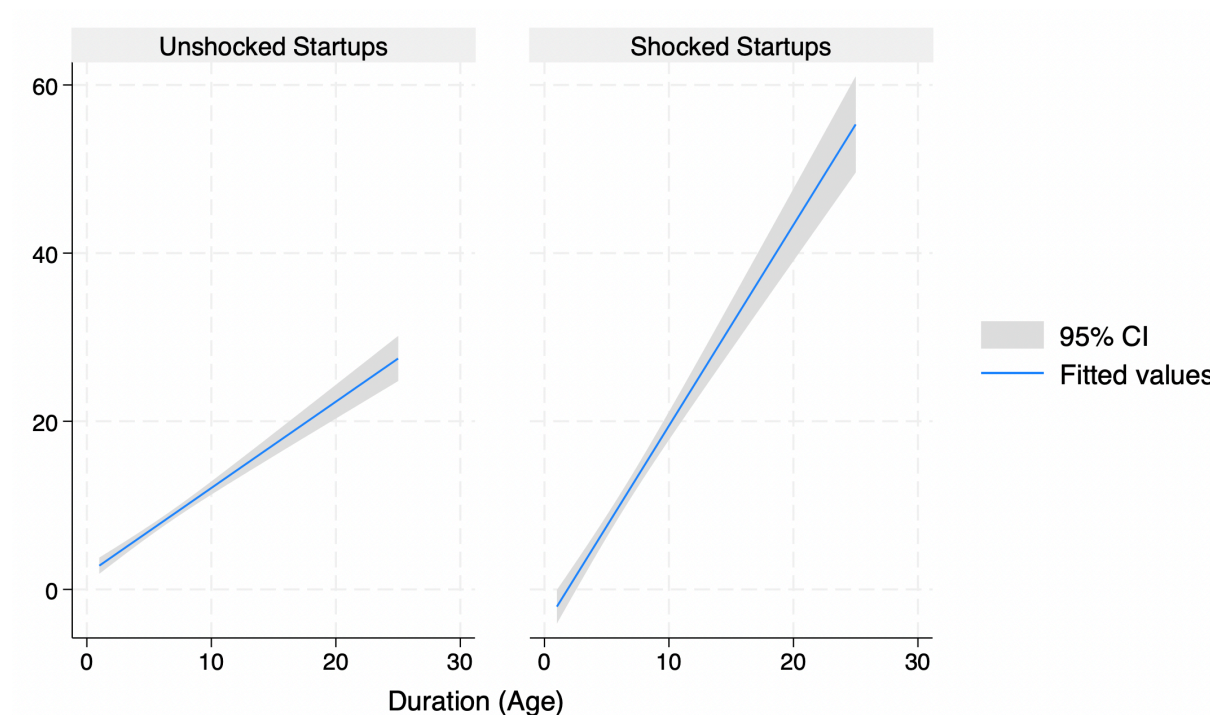
Appendix Figure A10: Differences between unshocked (left) and shocked (right) startups in the degree of hierarchy, i.e. ratio of TMT members to employees (y-axis) versus duration (i.e., startup age) on the x-axis (age truncated at 25 due to sparse data beyond that)



Appendix Figure A11: Differences between unshocked (left) and shocked (right) startups in Role Fluidity, i.e. number of employees per startup holding multiple concurrent roles within the startup (y-axis) versus duration (i.e., startup age) on the x-axis (age truncated at 25 due to sparse data beyond that)



Appendix Figure A12: Differences between unshocked (left) and shocked (right) startups in the number of employees with prior outside-industry work experience (y-axis) versus duration (i.e., startup age) on the x-axis (age truncated at 25 due to sparse data beyond that)



APPENDIX TABLES

Appendix Table A1: Models estimating technological change: Poisson models estimating the number of patent filings in a new 4-digit EPO class for startup-years in which the startup has at least one prior patent. ML estimates. Two-tailed tests. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

Specification:	(1) No FE on county	(2) With FE on county	(3) Shocked at later time	(4) Persistence of shock effects later in the startup's life	(5) Even more (locally) novel natural disaster in YPF
Indicator: encountered local natural disaster in year post founding	0.144** (0.047)	0.110* (0.047)		0.176** (0.065)	
Local natural disaster in 2 nd or 3 rd yr post founding (inclusive)			0.019 (0.046)		
Encountered more novel local natural disaster in year post founding					0.168*** (0.051)
Ln(cumulative patent applications filed by startup)	-0.453*** (0.022)	-0.458*** (0.021)	-0.458*** (0.021)	-0.518*** (0.031)	-0.458*** (0.021)
Num. EPO 4 digit classes the startup has filed in	0.075*** (0.006)	0.078*** (0.007)	0.078*** (0.007)	0.079*** (0.008)	0.078*** (0.007)
HHI concentration of patent filings	-2.296*** (0.085)	-2.330*** (0.091)	-2.323*** (0.091)	-2.590*** (0.134)	-2.335*** (0.091)
Funding raised in most recent round \$Bn (2010 dollars)	0.656*** (0.178)	1.243*** (0.231)	1.240*** (0.233)	1.252*** (0.264)	1.246*** (0.230)
Total equity funding till previous year \$Bn (2010 dollars)	-0.624*** (0.154)	-0.683*** (0.159)	-0.674*** (0.160)	-0.657*** (0.182)	-0.687*** (0.159)
Num. premier VCs among investors (by \$ deal volume)	-0.054 (0.042)	-0.073+ (0.039)	-0.069+ (0.039)	-0.035 (0.051)	-0.074+ (0.039)
Number of highly central Angel/VC investors	0.083+ (0.047)	0.079+ (0.041)	0.077+ (0.041)	0.072 (0.051)	0.080+ (0.041)
Total number of investors till last round	0.017** (0.006)	0.014* (0.006)	0.014* (0.006)	0.017+ (0.010)	0.013* (0.006)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	0.116** (0.044)	-0.019 (0.054)	-0.014 (0.054)	0.047 (0.069)	-0.020 (0.054)
Number of other startups in county (in hundreds)	0.133*** (0.025)	0.556*** (0.066)	0.556*** (0.066)	0.588*** (0.090)	0.557*** (0.067)
Square of number of other startups in county	-0.012*** (0.003)	-0.042*** (0.006)	-0.042*** (0.006)	-0.044*** (0.009)	-0.042*** (0.006)
Time Trend	-0.030*** (0.005)	-0.045*** (0.005)	-0.045*** (0.005)	-0.049*** (0.007)	-0.045*** (0.005)
Indicator for having multiple target segments	0.025 (0.062)	0.096 (0.064)	0.098 (0.064)	0.025 (0.087)	0.099 (0.064)
Indicator for B2B startup	-0.070 (0.059)	-0.037 (0.061)	-0.029 (0.061)	-0.065 (0.083)	-0.034 (0.061)
Indicator for B2Gov startup (<i>B2C startup is base category</i>)	-0.097 (0.420)	-0.182 (0.497)	-0.176 (0.492)	-0.114 (0.603)	-0.197 (0.493)
Constant	1.419*** (0.137)	1.599*** (0.375)	1.581*** (0.382)	1.791*** (0.387)	1.610*** (0.378)
Industry dummies	Yes	Yes	Yes	Yes	Yes
County dummies	No	Yes	Yes	Yes	Yes
Observations	15168	15168	15168	11457	15168
LL	-12943.643	-12512.889	-12519.178	-7908.075	-12506.486
Akaike Information Criterion	25931.285	25365.779	25378.356	16202.151	25352.971

Appendix Table A2: Supplementary tests of technological change. Model 6 is the Heckman first-stage model estimating whether the startup has at least one prior patent. Model 7 is the second-stage model estimating new-class patent filings among startup-years with at least one prior patent. Model 8 uses a discrete alternative measure of technological change. Two-tailed tests. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

Model comments:	(6) Heckman 1st stage predicting startup having ever patented at all	(7) Heckman 2nd stage predicting patenting in a new 4-digit EPO class	(8) Discrete outcome (any patents in new 4-digit EPO class)
Instrument: Number of patents filed by others in the focal startup's narrow sub-industry in the prior year	0.009*** (0.001)		
Indicator: encountered local natural disaster in year post founding	-0.078* (0.031)	0.060** (0.023)	0.078* (0.032)
Ln(cumulative patent applications filed by startup)		-0.296*** (0.013)	-0.135*** (0.014)
Num. EPO 4 digit classes the startup has filed in		0.125*** (0.013)	0.074*** (0.008)
HHI concentration of patent filings		-0.626*** (0.085)	-0.065+ (0.037)
Funding raised in most recent round \$Bn (2010 dollars)	0.111 (0.106)	0.342** (0.122)	0.080 (0.127)
Total equity funding till previous year \$Bn (2010 dollars)	-0.029 (0.040)	-0.356*** (0.103)	-0.145* (0.058)
Num. premier VCs among investors (by \$ deal volume)	-0.039 (0.025)	0.040+ (0.023)	0.060* (0.026)
Number of highly central Angel/VC investors	0.131*** (0.025)	-0.007 (0.022)	-0.120*** (0.027)
Total number of investors till last round	0.036*** (0.005)	0.009 (0.006)	-0.030*** (0.005)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.096*** (0.025)	0.022 (0.028)	0.120*** (0.027)
Number of other startups in county (in hundreds)	0.025 (0.016)	0.076*** (0.013)	0.013 (0.017)
Square of number of other startups in county	0.000 (0.002)	-0.007*** (0.002)	-0.003+ (0.002)
Time Trend	0.047*** (0.002)	-0.022*** (0.002)	-0.058*** (0.002)
Indicator for having multiple target segments	0.137** (0.046)	0.040 (0.030)	-0.117* (0.046)
Indicator for B2B startup	0.186*** (0.043)	-0.008 (0.027)	-0.189*** (0.043)
Indicator for B2Gov startup (<i>B2C startup is base category</i>)	0.398+ (0.225)	-0.146 (0.198)	-0.524* (0.216)
Industry indicators	Yes	Yes	Yes
Constant	-2.585*** (0.065)	1.601*** (0.111)	2.820*** (0.075)
Observations	135456	135456	135456
LL	-43396.828	-64523.635	-50380.932
Model chi2	1282.473***	1388.173***	1255.286***

Appendix Table A3: Supplementary tests of technological change. Model 9 is a random-effects Poisson model. Model 10 uses Mahalanobis distance between the startup's prior portfolio and its focal-year patent applications in a two-stage Heckman model. Model 11 restricts the sample to startup-years with at least two patents. Model 12 controls for novelty of the patent pool. QML and ML estimates. Two-tailed tests. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

Model comments:	(9) Random Effects on startup	(10) DV: log Mahalanobis distance	(11) Sample subset over having 2 or more patents	(12) Controlling for novelty of patent pool
Indicator: encountered local natural disaster in year post founding	0.105* (0.047)	0.125** (0.046)	0.148** (0.048)	0.353*** (0.057)
Ln(cumulative patent applications filed by startup)	-0.476*** (0.044)	0.262*** (0.015)	-0.449*** (0.021)	-0.463*** (0.021)
Num. EPO 4 digit classes the startup has filed in	0.102*** (0.017)	0.039*** (0.009)	0.075*** (0.006)	0.077*** (0.006)
HHI concentration of patent filings	-2.522*** (0.090)	-0.397*** (0.077)	-2.214*** (0.090)	-2.186*** (0.086)
Funding raised in most recent round \$Bn (2010 dollars)	1.110*** (0.239)	-0.016 (0.133)	0.655*** (0.178)	0.662*** (0.177)
Total equity funding till previous year \$Bn (2010 dollars)	-0.950*** (0.122)	0.065 (0.117)	-0.628*** (0.154)	-0.630*** (0.153)
Num. premier VCs among investors (by \$ deal volume)	-0.081+ (0.042)	-0.008 (0.047)	-0.050 (0.043)	-0.056 (0.041)
Number of highly central Angel/VC investors	0.064 (0.048)	0.050 (0.047)	0.076 (0.048)	0.087 (0.046)
Total number of investors till last round	0.013* (0.006)	0.001 (0.008)	0.018** (0.006)	0.018** (0.006)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	0.097+ (0.056)	-0.005 (0.048)	0.116* (0.046)	0.117** (0.044)
Number of other startups in county (in hundreds)	0.191*** (0.026)	0.086*** (0.024)	0.129*** (0.025)	0.133*** (0.024)
Square of number of other startups in county	-0.017*** (0.003)	-0.006* (0.003)	-0.012*** (0.003)	-0.012*** (0.003)
Time Trend	-0.063*** (0.005)	-0.031*** (0.004)	-0.030*** (0.005)	-0.030*** (0.005)
Indicator for having multiple target segments	0.089* (0.046)	0.016 (0.066)	0.021 (0.063)	0.031 (0.061)
Indicator for B2B startup	-0.058 (0.055)	-0.059 (0.065)	-0.073 (0.060)	-0.065 (0.058)
Indicator for B2Gov startup (<i>B2C startup is base category</i>)	-0.362 (0.473)	-0.155 (0.175)	-0.077 (0.440)	-0.004 (0.390)
Industry indicators	Yes	Yes	Yes	Yes
Constant	2.058*** (0.131)	1.069*** (0.182)	1.396*** (0.138)	1.374*** (0.135)
Observations	15168	135456	14449	15168
LL	-12367.794	-70822.412	-12559.259	-12884.485
Model chi2	4181.650***	1019.296***	2172.551***	2378.710***

Appendix Table A4: IPO analyses in samples with greater baseline IPO plausibility and predicted IPO propensity. Robust standard errors clustered by startup in parentheses. ML estimates. Two-tailed tests. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

	(13) Consumer-facing ventures	(14) Top quartile of predicted IPO propensity (static characteristics)	(15) Top quartile of predicted IPO propensity (full covariate set)	(16) Computer Science and Engineering ventures
Indicator: encountered local natural disaster in year post founding	0.063 (0.089)	-0.115 (0.100)	-0.022 (0.076)	0.122 (0.114)
Encountered disaster year post founding * Focal startup's industry <i>Hotness</i> \$Bn	0.858** (0.323)	0.806* (0.330)	0.596* (0.252)	0.585* (0.238)
Cumulative patent applications filed by startup	0.001 (0.000)	0.001*** (0.000)	0.000 (0.000)	0.001 (0.000)
HHI concentration of patent filings	-0.781*** (0.206)	-1.171*** (0.245)	-1.064*** (0.240)	-0.744** (0.229)
Funding raised in most recent round \$Bn (2010 dollars)	-0.178 (0.121)	-0.318* (0.139)	-0.134 (0.094)	-0.557*** (0.162)
Total equity funding till previous year \$Bn (2010 dollars)	0.317*** (0.078)	0.606*** (0.065)	0.242*** (0.066)	0.597*** (0.099)
Num. premier VCs among investors (by \$ deal volume)	0.162* (0.070)	0.074 (0.074)	0.042 (0.052)	0.239** (0.084)
Number of highly central Angel/VC investors	-0.066 (0.073)	0.005 (0.078)	-0.055 (0.055)	-0.027 (0.093)
Total number of investors till last round	0.057*** (0.011)	-0.003 (0.011)	-0.027** (0.009)	0.059*** (0.014)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.099 (0.142)	0.116 (0.142)	0.147 (0.127)	-0.150 (0.089)
Number of other startups in county (in hundreds)	-0.443*** (0.093)	-0.411*** (0.101)	-0.201* (0.082)	0.416** (0.135)
Square of number of other startups in county	0.043*** (0.009)	0.029** (0.010)	0.018* (0.008)	-0.031* (0.012)
Time Trend	-0.063*** (0.006)	-0.069*** (0.007)	-0.032*** (0.007)	-0.124*** (0.010)
Constant	0.584 (0.332)	0.852** (0.293)	-22.114 (NA)	-5.046*** (0.975)
Indicators for target segments (Multiple/B2B/B2Gov/B2C)		Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	
County dummies	Yes	Yes	Yes	Yes
Duration dependence of [Disaster <i>YPF</i> * Industry <i>Hotness</i>]	-0.140 (0.079)	-0.133 (0.078)	-0.076 (0.060)	-0.106* (0.053)
Ln(Shape parameter) or ancillary constant for duration dependence	0.822*** (0.026)	0.919*** (0.030)	0.766*** (0.028)	0.868*** (0.030)
Observations	59119	35705	33223	58229
LL	-2482.109	-1701.762	-2422.181	-1897.911
Akaike Information Criterion	5988.218	4151.525	4902.362	4523.822

Appendix Table A5: IPO analyses restricted to ventures with multiple recorded investors during the founding year. Models estimate IPO hazards among startups with more than one and more than two investors during that year. Robust standard errors clustered by startup in parentheses. ML estimates. Two-tailed tests. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

	(17) IPO hazards for >1 early investor	(18) IPO hazards for >2 early investors
Indicator: encountered local natural disaster in year post founding	0.039 (0.062)	0.018 (0.081)
Encountered disaster year post founding * Focal startup's industry <i>Hotness</i> \$Bn	0.619** (0.192)	0.910*** (0.202)
Cumulative patent applications filed by startup	0.000** (0.000)	0.000** (0.000)
HHI concentration of patent filings	-0.802*** (0.142)	-1.203*** (0.201)
Funding raised in most recent round \$Bn (2010 dollars)	-0.138 (0.098)	-0.153 (0.105)
Total equity funding till previous year \$Bn (2010 dollars)	0.339*** (0.075)	0.329*** (0.084)
Num. premier VCs among investors (by \$ deal volume)	0.187*** (0.047)	0.210*** (0.057)
Number of highly central Angel/VC investors	-0.056 (0.051)	-0.114 (0.062)
Total number of investors till last round	0.014 (0.008)	-0.014 (0.011)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.158* (0.078)	-0.075 (0.096)
Number of other startups in county (in hundreds)	-0.118 (0.071)	-0.113 (0.088)
Square of number of other startups in county	0.011 (0.007)	0.010 (0.008)
Time Trend	-0.076*** (0.005)	-0.076*** (0.006)
Constant	-23.167 (NA)	-23.111 (NA)
Indicators for target segments (Multiple/B2B/B2Gov/B2C)	Yes	Yes
Industry dummies	Yes	Yes
County dummies	Yes	Yes
Duration dependence of [Disaster YPF^i * Industry <i>Hotness</i>]	-0.081 (0.044)	-0.138** (0.045)
Ln(Shape parameter) or ancillary constant for duration dependence	0.804*** (0.019)	0.886*** (0.024)
Observations	115989	59782
LL	-5127.719	-2681.606
Akaike Information Criterion	10311.437	5423.213

Appendix Table A6: Supplementary tests, accounting for selection pressures (Model 19), and more locally novel natural disasters (Model 20): Weibull models estimating IPO hazards. Robust standard errors clustered by startup in parentheses. ML Estimates. 2-tailed tests. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

Dependent Variable:	(19) IPO hazard	(20) IPO hazard
Indicator: encountered local natural disaster in year post founding	0.002 (0.060)	
Encountered disaster year post founding* Focal startup's industry <i>Hotness</i> \$Bn	0.615*** (0.184)	
Number of local startups that failed in the focal startups founding year	-0.004*** (0.001)	
Encountered more novel local natural disaster in year post founding		0.084 (0.065)
Encountered novel disaster <i>YPF</i> * Focal startup's industry <i>Hotness</i> \$Bn		0.641** (0.202)
Cumulative patent applications filed by startup	0.000** (0.000)	0.000** (0.000)
HHI concentration of patent filings	-0.706*** (0.132)	-0.715*** (0.132)
Funding raised in most recent round \$Bn (2010 dollars)	-0.164+ (0.095)	-0.169 (0.095)
Total equity funding till previous year \$Bn (2010 dollars)	0.346*** (0.074)	0.349*** (0.073)
Num. premier VCs among investors (by \$ deal volume)	0.185*** (0.045)	0.186*** (0.045)
Number of highly central Angel/VC investors	-0.053 (0.049)	-0.058 (0.049)
Total number of investors till last round	0.035*** (0.008)	0.034*** (0.008)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.146* (0.074)	-0.108 (0.069)
Number of other startups in county (in hundreds)	-0.083 (0.067)	-0.103 (0.068)
Square of number of other startups in county	0.010 (0.006)	0.009 (0.006)
Time Trend	-0.072*** (0.005)	-0.076*** (0.005)
Indicators for target segments (multiple/B2B/B2Gov/B2C)	Yes	Yes
Constant	0.971*** (0.190)	0.982*** (0.182)
Industry dummies	Yes	Yes
County dummies	Yes	Yes
Duration dependence of [Disaster <i>YPF</i> * Industry <i>Hotness</i>]	-0.092* (0.044)	
Duration dependence of [More novel Disaster <i>YPF</i> * Industry <i>Hotness</i>]		-0.110* (0.051)
Ln(Shape parameter) or ancillary constant for duration dependence	0.788*** (0.018)	0.802*** (0.017)
Constant for duration dependence parameter (lnp)		
Observations	135456	135456
LL	-5780.855	-5785.974
Akaike Information Criterion	11627.710	11627.949

Appendix Table A7: Alternate models for IPO. Weibull hazards with county indicators.
Robust standard errors clustered by startup in parentheses. ML estimates. Two-tailed tests.
+ p < 0.1, * p < 0.05, ** p < 0.01, * p < 0.001**

Dependent Variable:	(21) IPO hazard	(22) IPO hazard
Log per capita damage from local natural disaster in year post founding	0.048 (0.042)	
Log per capita damage " * Focal startup's industry <i>Hotness</i> \$Bn	0.211* (0.084)	
Log per capita infrastructure damage from local natural disaster in year post founding		0.050 (0.056)
Log per capita infrastructure damage " * Focal startup's industry <i>Hotness</i> \$Bn		0.249** (0.097)
Cumulative patent applications filed by startup	0.000** (0.000)	0.000** (0.000)
HHI concentration of patent filings	-0.719*** (0.132)	-0.719*** (0.132)
Funding raised in most recent round \$Bn (2010 dollars)	-0.165 (0.096)	-0.166 (0.096)
Total equity funding till previous year \$Bn (2010 dollars)	0.345*** (0.074)	0.345*** (0.074)
Num. premier VCs among investors (by \$ deal volume)	0.191*** (0.045)	0.191*** (0.045)
Number of highly central Angel/VC investors	-0.064 (0.049)	-0.064 (0.049)
Total number of investors till last round	0.034*** (0.008)	0.034*** (0.008)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.050 (0.058)	-0.051 (0.058)
Number of other startups in county (in hundreds)	-0.107 (0.068)	-0.107 (0.068)
Square of number of other startups in county	0.010 (0.007)	0.010 (0.007)
Time Trend	-0.076*** (0.005)	-0.076*** (0.005)
Indicators for target segments (multiple/B2B/B2Gov/B2C)	Yes	Yes
Constant	0.869*** (0.168)	0.867*** (0.168)
Industry dummies	Yes	Yes
County dummies	Yes	Yes
Duration dependence of [Log per capita damage* Focal startup's industry <i>Hotness</i> \$Bn]	-0.090** (0.030)	
Duration dependence of [Log per capita infrastructure damage* Focal startup's industry <i>Hotness</i> \$Bn]		-0.104** (0.036)
Constant for duration dependence parameter (lnp)	0.797*** (0.017)	0.796*** (0.017)
Observations	135456	135456
LL	-5789.729	-5789.925
Akaike Information Criterion	11637.458	11695.850

Appendix Table A8: Alternate models for IPO. Clogit with county FE (23), RE logit with random effects on startup (24), Piecewise exponential hazards (25), and Cox proportional hazards (26). Robust standard errors clustered by county (23, 24) and by startup (25) in parentheses. QML estimates (23, 24), ML estimates (25, 26). Two-tailed tests. + p < 0.1, * p < 0.05, ** p < 0.01, * p < 0.001**

	(23)	(24)	(25)	(26)
Indicator: encountered local natural disaster in year post founding	0.036 (0.099)	0.067 (0.087)	0.058 (0.054)	0.078 (0.055)
Encountered disaster year post founding * Focal startup's industry <i>Hotness</i> \$Bn	0.233** (0.089)	0.204* (0.095)	0.239* (0.105)	0.403** (0.145)
Cumulative patent applications filed by startup	0.001* (0.000)	0.001** (0.000)	0.000** (0.000)	0.000** (0.000)
HHI concentration of patent filings	-0.626*** (0.137)	-0.597*** (0.131)	-0.642*** (0.128)	-0.660*** (0.128)
Funding raised in most recent round \$Bn (2010 dollars)	-0.275 (0.207)	-0.185 (0.230)	-0.100 (0.090)	-0.093 (0.092)
Total equity funding till previous year \$Bn (2010 dollars)	0.541** (0.183)	0.504* (0.246)	0.310** (0.081)	0.306** (0.082)
Num. premier VCs among investors (by \$ deal volume)	0.198*** (0.048)	0.184*** (0.050)	0.193*** (0.043)	0.179*** (0.043)
Number of highly central Angel/VC investors	-0.072 (0.050)	-0.053 (0.051)	-0.047 (0.047)	-0.048 (0.047)
Total number of investors till last round	0.056*** (0.011)	0.056*** (0.011)	0.042*** (0.008)	0.040*** (0.008)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.266*** (0.075)	-0.302*** (0.076)	-0.231** (0.071)	-0.199** (0.072)
Number of other startups in county (in hundreds)	-0.080 (0.127)	0.054 (0.048)	0.140** (0.031)	0.144*** (0.031)
Square of number of other startups in county	0.003 (0.009)	-0.004 (0.005)	-0.010** (0.004)	-0.010** (0.004)
Time Trend	-0.015 (0.010)	-0.024** (0.008)	-0.068*** (0.004)	-0.072*** (0.004)
Indicators for target segments (multiple/B2B/B2Gov/B2C)	Yes	Yes	Yes	Yes
Constant		-4.114*** (0.164)		
Industry dummies	Yes	Yes	Yes	Yes
County dummies	<i>Conditioned</i>	No	No	No
Duration dependence ("tvc") of Disaster YPF * Focal startup's industry <i>Hotness</i> \$Bn				-0.035 (0.020)
Observations	135456	135456	135456	135456
LL	-10411.940	-11097.725	-6432.941	-19194.012
Akaike Information Criterion	20865.881	22241.450	12929.882	38432.025

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
0	5,087	3.300501	.0616615	4.397893	3.179618	3.421384
Disaster	2,017	3.79876	.1275762	5.729575	3.548565	4.048955
Combined	7,104	3.441969	.0571679	4.818405	3.329903	3.554035
diff		-.498259	.1266569		-.7465443	-.2499737
diff = mean(0) - mean(Disaster)				t =	-3.9339	
H0: diff = 0				Degrees of freedom =	7102	
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0		
Pr(T < t) = 0.0000		Pr(T > t) = 0.0001		Pr(T > t) = 1.0000		

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
0	5,087	1.881148	.0496253	3.539439	1.783861	1.978435
Disaster	2,017	2.349402	.1066786	4.791047	2.14019	2.558614
Combined	7,104	2.014097	.0467553	3.940779	1.922443	2.105751
diff		-.4682536	.1035514		-.6712453	-.265262

diff = mean(0) - mean(Disaster) t = -4.5219

H0: diff = 0 Degrees of freedom = 7102

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

Pr(T < t) = 0.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 1.0000

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
0	5,026	2.643422	.0947989	6.720697	2.457574	2.829269
Disaster	1,925	1.715162	.0758772	3.329099	1.566352	1.863972
Combined	6,951	2.386351	.071864	5.991491	2.245475	2.527226
diff		.9282598	.16022		.6141796	1.24234
diff = mean(0) - mean(Disaster)				t =	5.7937	
H0: diff = 0				Degrees of freedom =	6949	
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0		
Pr(T < t) = 1.0000		Pr(T > t) = 0.0000		Pr(T > t) = 0.0000		

Appendix Table A10: GSEM (Simultaneous) Models. Robust standard errors clustered by startup in parentheses. Two-tailed tests + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, * $p < 0.001$**

DV:	27(a) IPO	27(b) New class patenting	27(c) Failure	27(d) Buyout	27(e) Log Mahalan obis distance Linear
GSEM Link	Logit	Poisson	Logit	Logit	
Indicator: encountered local natural disaster in year post founding	0.063 (0.057)	0.144** (0.047)	0.133* (0.065)	0.119* (0.055)	0.108* (0.046)
Encountered disaster <i>YPF</i> * Focal startup's industry <i>Hotness</i> \$Bn	0.218* (0.110)			0.008 (0.065)	
Cumulative patent applications filed by startup	0.001*** (0.000)	-0.453*** (0.022)	-0.002+ (0.001)	-0.012* (0.006)	0.262*** (0.015)
HHI concentration of patent filings	-0.679*** (0.133)	-2.296*** (0.085)	-0.793*** (0.234)	-0.515** (0.169)	-0.395*** (0.077)
Funding raised in most recent round \$Bn (2010 dollars)	-0.102 (0.177)	0.656*** (0.178)	-0.666+ (0.354)	-0.881*** (0.255)	0.013 (0.126)
Total equity funding till previous year \$Bn (2010 dollars)	0.398* (0.158)	-0.624*** (0.154)	0.176+ (0.095)	0.176* (0.083)	0.054 (0.119)
Num. premier VCs among investors (by \$ deal volume)	0.202*** (0.048)	-0.054 (0.042)	0.028 (0.064)	0.134** (0.046)	-0.016 (0.046)
Number of highly central Angel/VC investors	-0.053 (0.051)	0.083+ (0.047)	0.175** (0.066)	0.126** (0.048)	0.079+ (0.045)
Total number of investors till last round	0.038*** (0.010)	0.017** (0.006)	-0.034* (0.013)	-0.015+ (0.008)	0.009 (0.008)
Equity capital flows into the focal startup's industry in year (<i>Hotness</i>) \$Bn	-0.215** (0.073)	0.116** (0.044)	0.768*** (0.043)	0.413*** (0.040)	-0.032 (0.048)
Number of other startups in county (in hundreds)	0.153*** (0.033)	0.133*** (0.025)	0.281*** (0.042)	0.192*** (0.028)	0.093*** (0.023)
Square of number of other startups in county	-0.011** (0.004)	-0.012*** (0.003)	-0.017*** (0.005)	-0.012*** (0.003)	-0.006* (0.003)
Time Trend	-0.076*** (0.005)	-0.030*** (0.005)	-0.136*** (0.005)	-0.090*** (0.003)	-0.019*** (0.003)
Indicator for having multiple target segments	-0.144* (0.067)	0.025 (0.062)	-0.542*** (0.104)	-0.339*** (0.075)	0.053 (0.066)
Indicator for B2B startup	-0.187** (0.061)	-0.070 (0.059)	-0.210** (0.081)	0.139* (0.062)	-0.007 (0.064)
Indicator for B2Gov startup (<i>B2C startup is base category</i>)	-1.212* (0.540)	-0.097 (0.420)	-1.962+ (1.011)	-0.255 (0.351)	-0.057 (0.162)
Duration dependence (log duration) for hazard-analog models (using logit in GSEM)	1.219*** (0.036)		0.109* (0.049)	0.414*** (0.031)	
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Constant	-5.340*** (0.109)	1.419*** (0.137)	-3.441*** (0.122)	-3.500*** (0.088)	0.259* (0.125)

Simultaneous model stats: Log Pseudolikelihood: -68933.657, Akaike Information Criterion: 138093