Online Appendix

A Additional Tables

Table A1: Pre-treatment Growth of Surviving Firms

	employment	*revenues*
Treated	.007251	.00189
	(.006282)	(.006259)
NAICS4 FE	Y	Y
Birth Yr FE	Y	Y
Firm Age FE	Y	Y
R^2	.07916	.102
N	20500	14000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry, cohort, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Employment and Revenue show the TVV/DHS change in Employment and Revenue between firm birth and the year prior to the premature death, respectively.

Table A2: Robustness of Death Shock Effects to Fixed Effects

	dhs(emp)	*dhs(emp)*	*dhs(emp)*
Post × Treated	-.05803***	-.05853***	-.0582***
	(.009735)	(.009704)	(.009745)
Post × Treated × Founder	-.2304***	-.2306***	-.2341***
	(.01453)	(.01448)	(.01449)
R^2	.3827	.3961	.4381
N	316000	316000	316000
Fixed Effects			
Year	Y	Y	N
NAICS4 × Year	N	Y	N
NAICS4 × Firm Age	Y	Y	N
NAICS4 × Firm Age × Year	N	N	Y
Firm	Y	Y	Y

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Each column shows estimates controlling for different combinations of fixed effects. Our preferred estimates control for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Regression specifications also include *Post* and *Post* × *Founder*, the estimates for which are excluded for simplicity.

Table A3: Robustness of B2B Death Shock Effects to Fixed Effects

	dhs(emp)	*dhs(emp)*	*dhs(emp)*
Post × Treated	-.03939**	-.03839**	-.03741**
	(.01216)	(.01213)	(.01213)
Post × Treated × Founder	-.2222***	-.2234***	-.2266***
	(.01878)	(.01869)	(.01862)
Post × Treated × B2B	-.04058**	-.04389**	-.04535**
	(.01981)	(.01975)	(.01985)
Post × Treated × B2B × Founder	-.01624	-.01394	-.0144
	(.02937)	(.02928)	(.02933)
R^2	.3827	.3961	.4382
N	316000	316000	316000
Fixed Effects			
Year	Y	Y	N
NAICS4 × Year	N	Y	N
NAICS4 × Firm Age	Y	Y	N
NAICS4 × Firm Age × Year	N	N	Y
Firm	Y	Y	Y

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Each column shows estimates controlling for different combinations of fixed effects. Our preferred estimates control for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Regression specifications also include *Post* and $Post \times B2B$, the estimates for which are excluded for simplicity.

Table A4: Death Shocks and Very Young Firms

	$dhs(emp)$	$dhs(rev)$
Post × Treated	-.04302**	-.06183**
	(.01779)	(.02082)
Post × Treated × Founder	-.3004***	-.2921***
	(.02731)	(.03506)
Post × Treated × Fage 2-5	-.02076	.0005993
	(.02116)	(.02513)
Post × Treated × Fage 2-5 × Founder	.08656**	.02078
	(.03203)	(.04145)
R^2	.391	.4148
N	316000	204000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Regressions specifications also include $Post$ and $Post \times Fage\ 2-5$, the estimates for which are excluded for simplicity. The dummy variable $Fage\ 2-5$, which identifies firms treated at firm age 2-5, excludes and is mutually exclusive of firms treated at firm age $0-1$.

Table A5: Correlation of Skill Measures

	High Tech	Abstract Task	College Share
High Tech	1		
Abst Task	.005244	1	
College	.4027	.5041	1

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Table shows correlation coefficients between the industry-level measures High Tech, Abstract Task, and College Share.

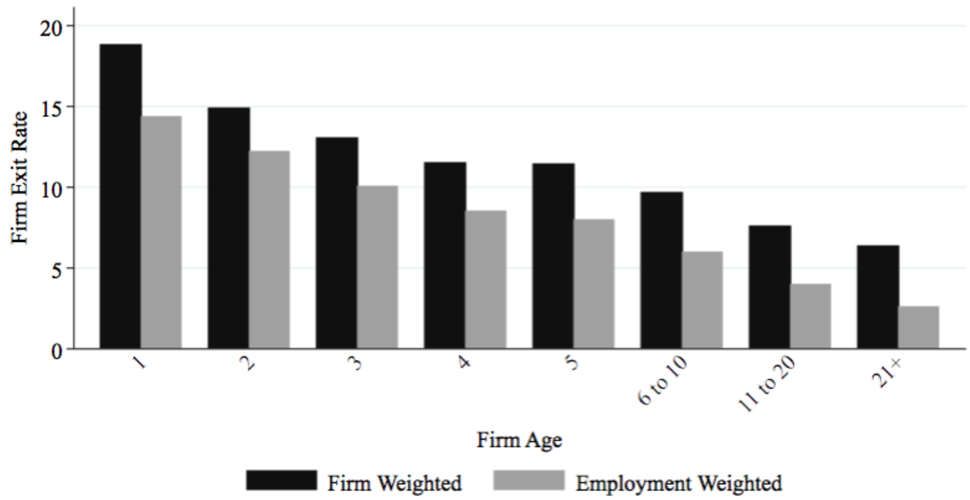
Table A6: Small Business Intensive Sectors

	$dhs(emp)$	$dhs(rev)$
Post × Treated	-.05948***	-.05634***
	(.01138)	(.01398)
Post × Treated × Founder	-.2092***	-.263***
	(.01783)	(.02355)
Post × Treated × HP	.002342	-.01895
	(.02191)	(.02653)
Post × Treated × HP × Founder	-.05674*	-.02769
	(.03106)	(.04076)
R^2	.3908	.4147
N	316000	204000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Regressions specifications also include $Post$ and $Post \times HP$, the estimates for which are excluded for simplicity. HP is equal to 1 if the firm is in a HP sector and zero otherwise.

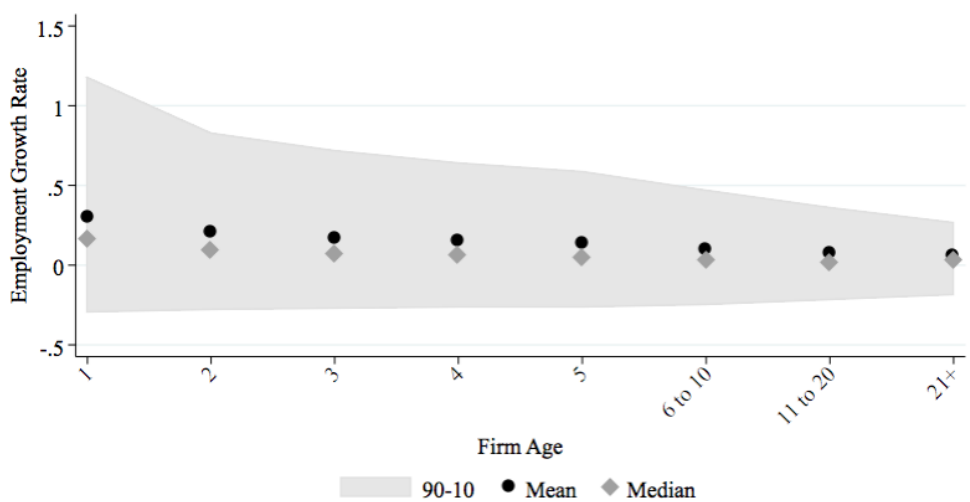
B Additional Figures

Figure B1: Firm Exit Rates and Firm Age



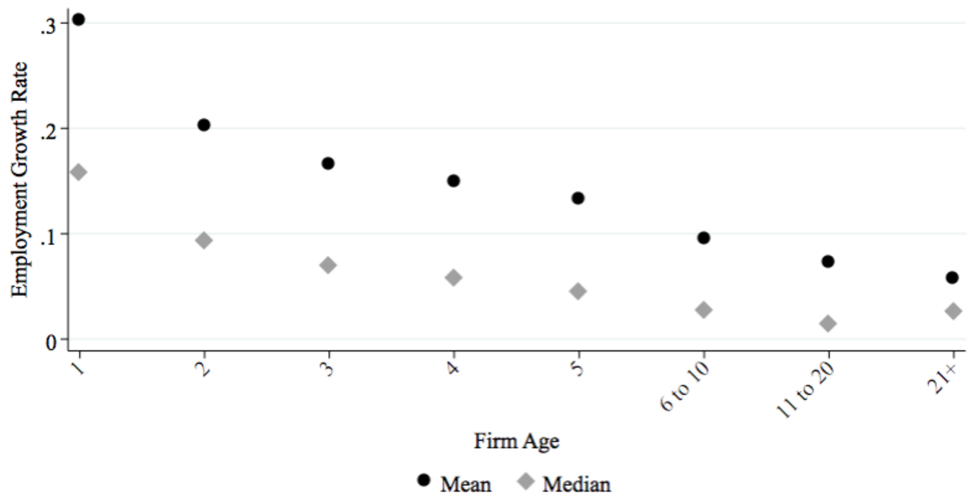
Source: Initial Team Database (LBD, LEHD), author's calculations.

Figure B2: Firm Age and Employment Growth



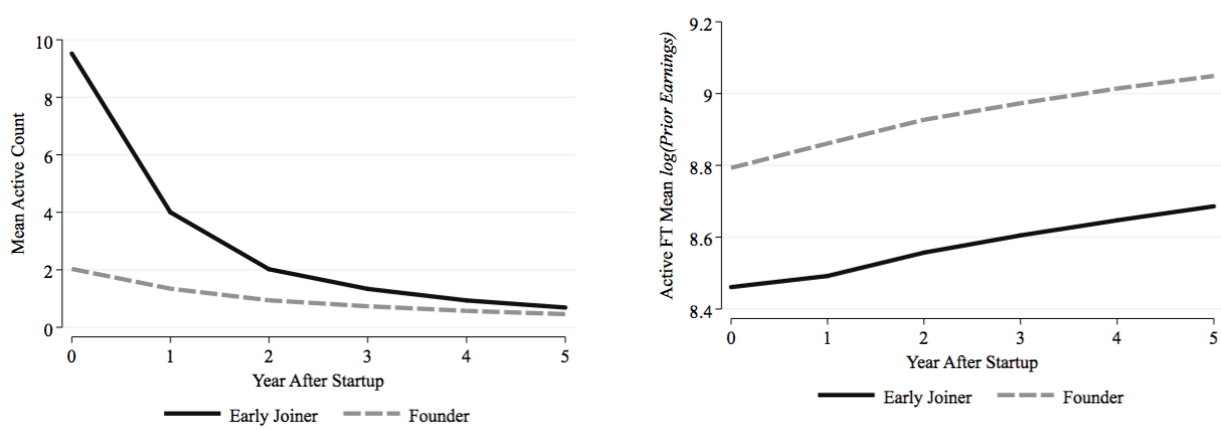
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Employment-weighted distribution.

Figure B3: Firm Age and Mean and Median Employment Growth



Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Employment-weighted distribution.

Figure B4: Founder and Early Joiner Attrition and Prior Earnings

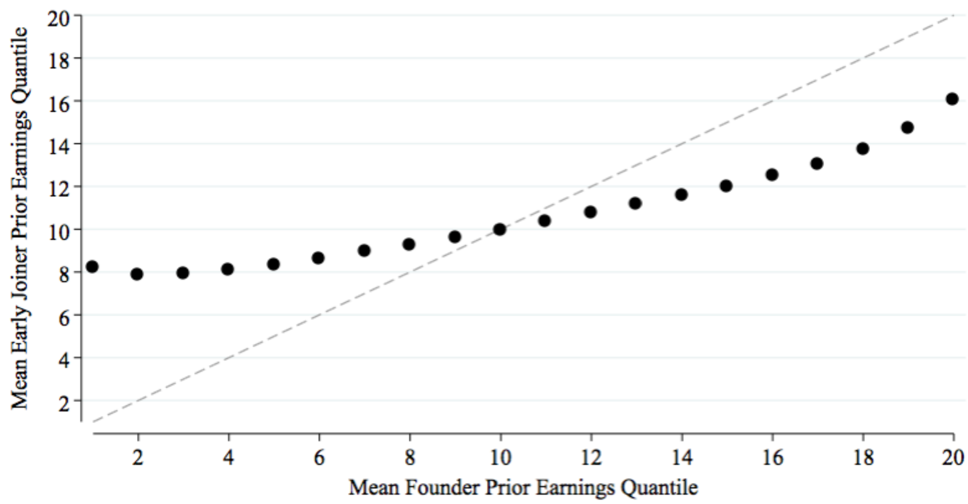


(a) Attrition of Founders, Early Joiners

(b) Prior Earnings of Active Founders, Early Joiners

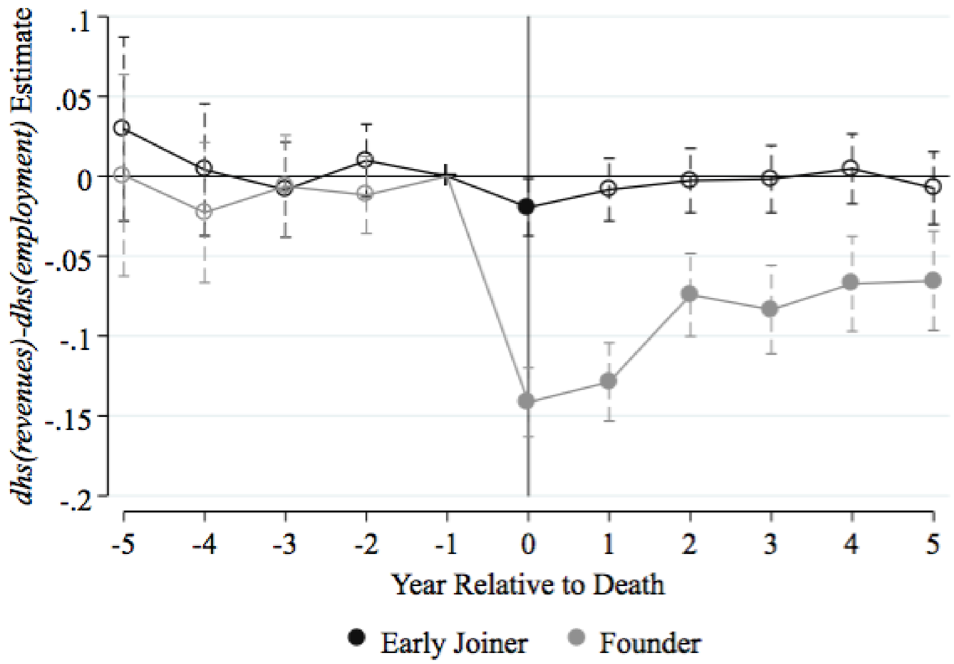
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Mean count of active (earnings positive) founders and early joiners each year after startup (a) and mean active founder and early joiner log prior earnings (b).

Figure B5: Prior Earnings Composition of Founders and Early Joiners



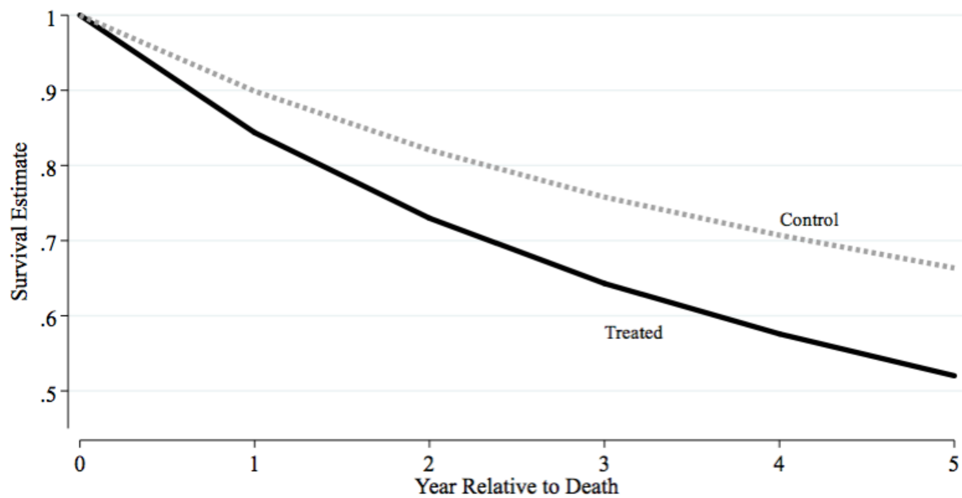
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Mean early joiner prior earnings quantile bin for each founder prior earnings quantile bin. 45° shown to emphasis when founder prior earnings position is equal to early joiner prior earnings position.

Figure B6: Initial Teams Death Shocks and $dhs(revenues) - dhs(employment)$



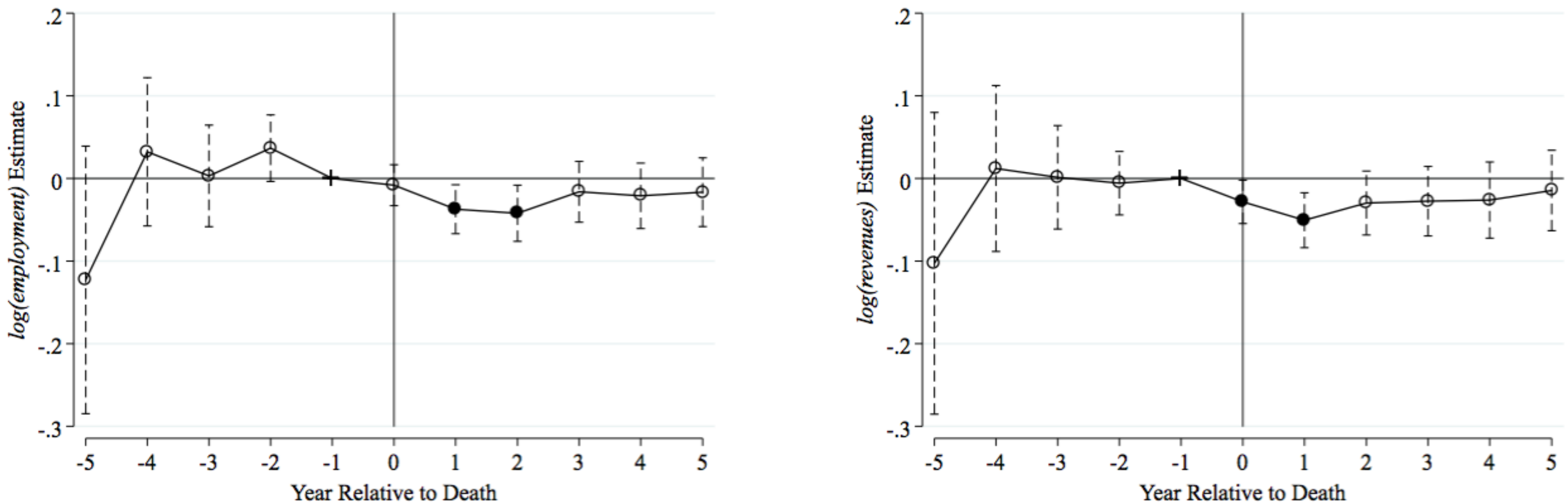
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t-1$. Points shifted around time periods, early joiner left and founder right, to ease interpretation.

Figure B7: Initial Team Death Shocks and Cox Survival Estimates



Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Cox estimate 0.35 (0.013). Controlling for firm age, industry, state, and year.

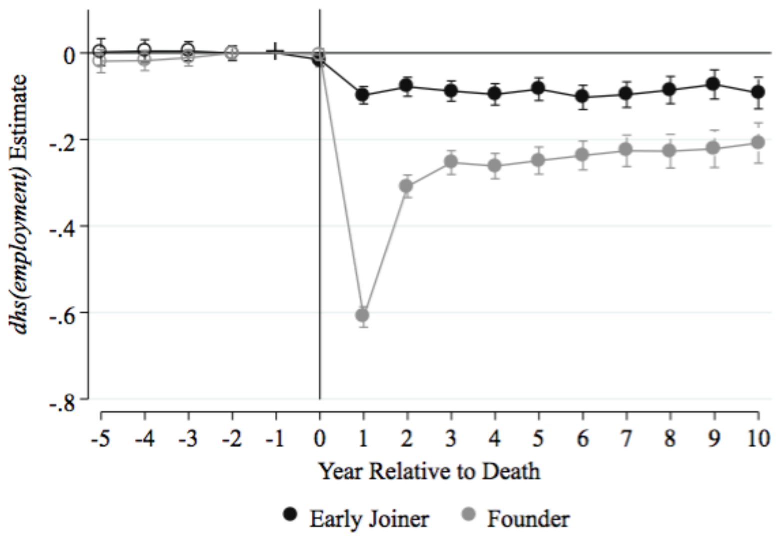
Figure B8: Impact of Second Year Joiners Death on *log* Outcomes



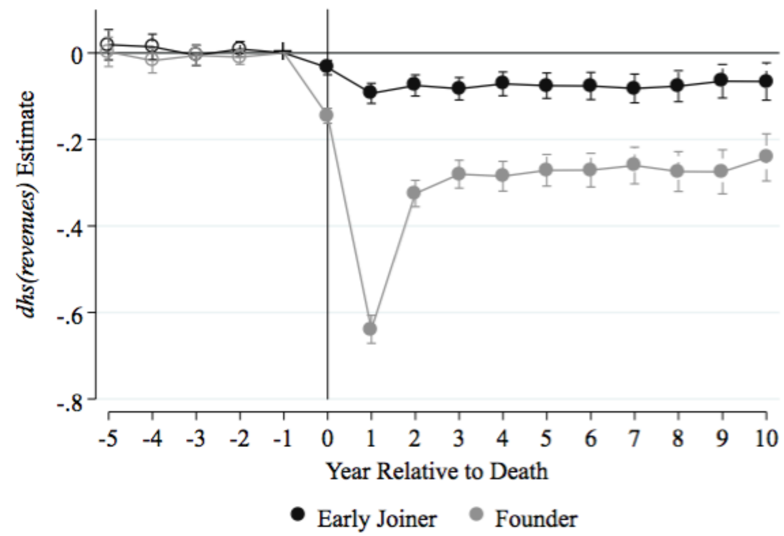
(a) Employment (b) Revenues

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t-1$.

Figure B9: Persistence of Death Shocks



(a) Employment



(b) Revenues

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t-1$.

C Model

In this appendix, we develop an illustrative two-period model of selection and size based on the formation of organization capital by initial teams. To start a business, an entrant pays a fixed entry fee in a formation period with a initial team devoting time and resources to develop organization capital. Let the number of initial team members be given by N. initial team members are ex ante homogeneous but are heterogeneous in terms of their ex post match quality for developing organization capital. We intentionally focus initially on a specification without heterogeneity among initial team members to highlight the potential role of the initial team even without such effects. We discuss extensions with heterogeneity (i.e., distinguishing between founders and early joiners) below.

This setting provides a novel way to interpret the ex ante fixed cost of entry in standard models. Here it is given by $w_0 N$, where w_0 is the market wage paid to the initial team in the formation phase. That is, decisions about the initial team play a role of the fixed entry fee. In period 0, the formation phase, the initial team invests in organization capital such that the firm in turn obtains a draw M_{i1} from a distribution of initial team match quality. The initial team is also subject to exogenous idiosyncratic attrition before the production period at a rate $(1 - \chi_{i1})$. This attrition impacts the available initial team members as well as the productivity for period 1. Productivity (technical efficiency) in period 1 is given by $M_{i1}(1-\chi_{i1})^{\kappa}$. The parameter κ captures the knowledge decay from the (exogenous) attrition of initial team members. If $\kappa = 0$, then there is no decay, so the organization capital created in the formation period is not embodied in the initial team. However, as κ increases there is positive decay. Given the exogenous idiosyncratic attrition the maximum number of initial team members available as employees in the production phase period 1 is $L_{i1}^{IT} \leq (1 - \chi_{i1}) N$. Thus, the maximum share of initial team members available in period 1 is $1 - \chi_{i1}$.

In period 1, the firms decide whether to produce or exit and then, if they produce, how many workers to employ. The revenue function is given by

$$R_{i1} = M_{i1}(1 - \chi_{i1})^{\kappa}(L_{i1}^{IT} + \gamma L_{i1}^{NT} - f)^{\theta}, \tag{1}$$

where L_{i1}^{NT} is the number of non-initial team members, $\theta < 1$ representing curvature in the revenue function (from product differentiation or DRS), $\gamma \leq 1$ is a parameter reflecting the assumption that non-initial team members may be less productive in implementing the organization capital, and f reflects fixed costs of production captured by overhead labor. With this revenue function, the marginal revenue product of initial team members always exceeds that of non-initial team members as long as $\gamma < 1$. This formulation does not have any knowledge capital decay from endogenous attrition of initial team members. Adding this feature enhances the results discussed below but yields less transparent decision rules. In this more general case, initial team members have higher marginal revenue products than non-initial team members from this extra effect on productivity.

The profit function is given by

$$\pi_{i1} = M_{i1}(1 - \chi_{i1})^{\kappa}(L_{i1}^{IT} + \gamma L_{i1}^{NT} - f)^{\theta} - w_1(L_{i1}^{IT} + L_{i1}^{NT}), \tag{2}$$

where w_1 is the market wage paid to the workers in the production period.[1]

[1] As IT members are more productive, it might be that the surplus is shared between the firm and initial team members. We assume for simplicity that the firm gets all the surplus.

The first-order conditions for initial team and non-initial team employment if the firm produces are given by

$$M_{i1}(1-\chi_{i1})^{\kappa}\theta(L_{i1}^{IT}+\gamma L_{i1}^{NT}-f)^{\theta-1}-w_1-\lambda=0 \tag{3}$$

$$M_{i1}(1-\chi_{i1})^{\kappa}\theta\gamma(L_{i1}^{IT}+\gamma L_{i1}^{NT}-f)^{\theta-1}-w_1=0, \tag{4}$$

where λ is the multiplier for the constraint $L_{i1}^{IT}\leq(1-\chi_{i1})N$. It is apparent that for $\gamma<1$, $L_{i1}^{NT}>0$ only if $\lambda>0$. This result implies we can simplify these first-order conditions for the ranges where only the initial team are employed and when non-initial team members are employed.

If only initial team members are employed and the constraint is not binding, the optimal number of initial team members to employ is given by

$$L_{i1}^{IT}=(M_{i1}(1-\chi_{i1})^{\kappa}\theta/w_1)^{1/(1-\theta)}+f. \tag{5}$$

Revenues are given by

$$R_{i1}=(M_{i1}(1-\chi_{i1})^{\kappa}(M_{i1}(1-\chi_{i1})^{\kappa}\theta/w_1)^{\theta/(1-\theta)}. \tag{6}$$

Observe that as either M_{i1} declines or χ_{i1} increases, employment and revenue decline. Also, revenue productivity R_{i1}/L_{i1}^{IT} in this range is given by

$$R_{i1}/L_{i1}^{IT}=(w_1/\theta)(1-f/L_{i1}^{IT}). \tag{7}$$

This outcome implies that as M_{i1} declines or χ_{i1} increases, revenue productivity declines. It is useful to note that the implications for revenue productivity depend on the fixed costs of operations being specified in terms of overhead labor. The implications for scale (either employer or revenue) are robust to the fixed costs being specified as an external cost rather than overhead labor

In addition, profits are given by

$$\pi_{i1}=L_{i1}^{IT}(w_1(1/\theta-1))-fw_1/\theta. \tag{8}$$

Thus, for sufficiently low M_{i1} or sufficiently high χ_{i1}, profits will become negative and the firm will exit. That is, either shock will lower employment, and at sufficiently low employment the firm cannot cover its fixed costs.

For the range where the constraint is binding (that is, $L_{i1}^{IT}=(1-\chi_{i1})\,N$), the decision rules depend on whether it is profitable to produce using non-initial team members. The optimal number of non-initial team members, conditional on producing, is given by

$$L_{i1}^{NT}=\frac{1}{\gamma}[(M_{i1}(1-\chi_{i1})^{\kappa}\theta\gamma/w_1)^{1/(1-\theta)}+f-(1-\chi_{i1})N]. \tag{9}$$

Revenue is given by

$$R_{i1}=(M_{i1}(1-\chi_{i1})^{\kappa}(M_{i1}(1-\chi_{i1})^{\kappa}\theta\gamma/w_1)^{\theta/(1-\theta)}. \tag{10}$$

Revenue labor productivity is given by

$$R_{it}/L_{i1}^{tot} = (w_1/\theta)(1 - f/L_{i1}^{tot}), \tag{11}$$

where $L_{i1}^{tot} = L_{i1}^{IT} + L_{i1}^{NT}$. In this range, a decrease in M_{i1} or increase in χ_{i1} yields a decrease in employment, revenue, and revenue labor productivity. That is, either will lower employment, and the overhead costs will be spread over a smaller number of workers yielding lower productivity. Again the revenue productivity implications depend on the fixed cost of operations being specified via overhead labor. Profits are given by

$$\pi_{i1} = L_{i1}^{tot}(w_1(1/\theta - 1)) - fw_1/\theta. \tag{12}$$

With sufficiently low M_{i1} or sufficiently high χ_{i1}, profits will become negative and the firm will exit. Observe as well that as χ_{i1} rises, the constraint on the number of initial team members will be more likely to bind, which provides some incentive to replace them in production with non-initial team members. However, an offsetting factor is that as χ_{i1} increases, the marginal product of workers declines. It is important to observe that all of these implications for χ_{i1} depend on $\kappa > 0$. Attrition of the initial team matters for employment, revenue, productivity, and exit only if the organization capital knowledge is embodied in the initial team members.

Entry is determined as in the standard model by a free entry condition. Firms enter until the present discounted value of future profits equals the fixed cost of entry

$$\int\int max(\pi_{i1}, 0)g(M_{i1})h(\chi_{i1})dM_{i1}d\chi_{i1} - w_0N = 0, \tag{13}$$

where, for simplicity, no discounting is assumed. This free entry condition helps make clear that our modified model is in many ways a re-interpretation of the standard model. The fixed entry fee is paying for the time and resources of the formation period when organization capital is developed by the initial team. The ex post productivity realizations depend on the stochastic success of the initial team and the exogenous attrition of the initial team.

The model collapses to the standard model if $\kappa = 0$ and $\gamma = 1$. In this case the model becomes a minor re-interpretation of what is involved in paying the fixed cost of entry in order to obtain the ex post productivity draw. The novel feature of the model is the hypothesis that the organization capital developed in the formation phase is embodied in (at least some) of the initial team members.

We now consider extensions of the model to allow heterogeneity among the founding team designating some as founders and others as early joiners Suppose that the initial team is still of size N with ω the fraction of the initial team that are founders and $1 - \omega$ the fraction that are early joiners. For simplicity, we assume the general human capital is the same for founders and early joiners but this could be modified. Both founders and early joiners are subject to exogenous attrition (assumed for simplicity to be equal) but the decay rate is assumed to differ with $\kappa_F >= \kappa_{EJ}$. That is, the organization capital is potentially embedded to a greater degree with founders. Technical efficiency in period 1 is given by: $TFPQ_{i1} = [\omega(1 - \chi_{i1})^{\kappa_F} + (1 - \omega)(1 - \chi_{i1})^{\kappa_{EJ}}]$Revenue is given by

$$R_{i1} = TFPQ_{i1}(L_{i1}^{IT} + \gamma_{EJ}L_{i1}^{EJ} + \gamma_{NT}L_{i1}^{NT} - f)^{\theta}. \tag{14}$$

In this formulation, founders are preferred to early joiners and $\gamma_{EJ} >= \gamma_{NT}$ so that early joiners are potentially preferred to non-initial team members. In the case that $\kappa_{EJ} = 0$ and $\gamma_{EJ} = \gamma_{NT}$, there is nothing special about the unskilled initial team members. They might be necessary as an input during the formation period, but they are perfect substitutes with non-initial team members thereafter. In contrast, as κ_{EJ} approaches κ_F then the loss of an early joiner becomes increasingly like the loss of a founder (and relatedly as γ_{EJ} approaches one).

The simple model along with extensions sketched in this appendix is intended to be illustrative. While this framework helps relate the potential role of organization capital formation to founders and early joiners, the framework neglects some important features that we have found empirically. For example, we find that early joiners become more important as a firm ages from being very young (age 5 or less) to being still young but older (age 6 to 11). This finding suggests that the contribution of early joiners to organization capital becomes more important over time. In terms of the model, this would suggest adding dynamic accumulation that reinforces the embodied organization capital in early joiners

D Data Infrastructure

This data appendix includes a more detailed description with accompanying references of the data infrastructure.

Information on startups is derived from the LBD (Jarmin and Miranda, 2002; Chow et al., 2021). The LBD tracks annually all U.S. nonfarm establishments and firms with at least one paid employee. An establishment is identified as a specific physical location where business activities occur, and all establishments under common operational control are grouped under the same firm identifier. The primary source of information on operational control is the Company Organization Survey (conducted annually) and the Economic Censuses (conducted every five years). Information in the LBD includes the number of employees, annual payroll, industry, establishment and firm age, and entry and exit of establishments and firms. We enhance these data by incorporating revenue information imported from the Business Register (BR) as in Haltiwanger et al. (2017). While revenue is available for only about 80 percent of the LBD, Haltiwanger et al. (2017) find that revenue is missing approximately at random. Following LBD conventions, we define firm age as the age of the oldest establishment in the firm's first year with positive employment. Startups are defined as firms with age zero, and firm death occurs when the firm and all associated establishments exit and are not observed again with employment. This approach avoids classifying exit through acquisition as a firm death.[2] Our outcome variables of interest are employment, revenue, and survival.[3]

[2] In certain cases, firm identifiers in the LBD are not longitudinally consistent. Firm identifiers may change for a number of reasons unrelated to a change in common ownership, such as a transition from a single- to a multi-unit firm, reorganization of the legal form and acquisitions. In our startup panel, we construct a longitudinally consistent firm identifier by leveraging information on establishment flows, EINs, and business names. Importantly, our longitudinal firm identifier will not longitudinally link a firm before and after an acquisition event.

[3] Employment consists of full- and part-time employees, including salaried officers and executives of corporations, who were on the payroll in the pay period including March 12. Revenue is measured as total revenue measured annually. Appropriate caution is needed in interpreting descriptive results using revenue

Our data contain sole proprietors and corporations where we can consistently include active business owners in our measure of the initial team. We define the initial team as all individuals with positive unemployment insurance (UI) covered earnings at the startup within the firms' first year of operation as well as business owners of sole proprietors. Owners of sole proprietors and partnerships are prohibited from paying themselves wages and therefore do not appear in the LEHD. Sole proprietors file self-employment income tax filings, which are captured in the BR. We are therefore able to combine sole proprietor owners with the initial teams recovered from the LEHD. Active or managing owners of partnerships, however, file Schedule K-1 pass-through income that will not be observed in either the BR or the LEHD. We therefore exclude partnerships from our startup sample.

For C or S corporations, the vast majority of active founders/owners are likely to be included among the individuals with positive UI earnings in the LEHD. The Internal Revenue Service (IRS) requires that owners of C or S corporations who provide more than minor services to their corporations receive employment compensation. For example, Internal Revenue Service (2022*b*) states "The definition of an employee under the Internal Revenue Code includes corporate officers. Courts have consistently held S corporation officers/shareholders who provide more than minor services to their corporation and receive, or are entitled to receive, compensation are subject to federal employment taxes.". Indeed, using K-1 and W-2 filings data, Nelson (2016) finds about 84 percent of all S corporations with paid employees have at least one shareholder employee. The restriction to businesses with paid employees (our focus) is crucial. There are a large number of non-employer S corporations. Nelson (2016) reports that about 39% of all S corporations have no employees. We exclude non-employers from our analysis. Furthermore, Nelson (2016) documents that privately held C corporations "appear to pay out a majority of the owners' income in the form of executive compensation" and virtually all C corporation startups are privately held. Also, see Internal Revenue Service (2022*a*), which states that "An officer of a corporation is generally an employee, but an officer who performs no services or only minor services, and who neither receives nor is entitled to receive any pay, is not considered an employee." This clarification helps explain why some K-1 owners of S corporations do not show up in the W-2 as employees. We regard such owners as passive owners of less interest to our analysis. Therefore, for the vast majority of the startups in our data, our measurement methodology of initial teams is likely to capture both active business owners and the earlier joining employees.

To identify founders, we largely follow the approach used in previous studies based on workers' earnings and the legal form of the startup (for example, Kerr and Kerr 2017; Choi 2017; Azoulay et al. 2020; Kim 2022). For corporations, we define founders as those who earn wages in the first quarter of the firm's operations (that is, they are present on "day one") and are among the three highest-paid workers in the firm during the first year. For sole proprietorships, because owners are not observed in the LEHD, we define founders as the business owner and the top two workers with the highest earnings in the first year. In addition, we define early joiners as the remaining employees at the startup in its first year

labor productivity. While the evidence shows that revenue labor productivity is positively correlated with technical efficiency and demand shocks (see, e.g., Decker et al. (2020)), variation in revenue labor productivity across firms can reflect frictions and distortions. For these reasons in our main causal analysis we focus on measures of scale and survival as key outcomes. Scale and survival are more likely directly related to technical efficiency and demand shocks.

of operations. An important distinction is that, unlike founders, who are present in the first quarter, early joiners may join in subsequent quarters during the initial year of the firm.

Our measurement approach overcomes pitfalls in identifying founders in the administrative data (Hyatt, Murray and Sandusky, 2021). First, we abstract from partnerships that do not earn wage and salary income from their business. Second, we use auxiliary source information from the BR to identify owners of sole proprietors. For corporations, conditional on an owner appearing as employee, both Azoulay et al. (2020) and Hyatt, Murray and Sandusky (2021) find that 85 to 90 percent of S corporation owners identified by K-1 filing data also appear in the W-2 and LEHD data as one of the top three earners during the firms' first year. Nelson (2016) and Hyatt, Murray and Sandusky (2021) find a similar share of S corporations to have at least one owner employee, 84 and 83 percent respectively.[4]

Our definition of founders likely includes owners but also initial team member employees that are likely to hold a leadership position within the firm regardless of whether they have a financial stake in the firm. Concerns around properly identifying founders are further allayed by our empirical findings. In particular, the negative impact of losing a initial team member is more pronounced when losing a founder than when losing an early joiner, though both cases yield negative and significant effects. Our measure appears to capture the outsized role that founders typically have on their firms relative to early joiners. For our purposes, we are especially interested in the contribution of early joiners. Based on the evidence, it is very unlikely that business owners are classified as early joiners.

E Alternative Transformations of Dependent Variable

We use the TVV/DHS measure of relative change as our primary outcome in our analysis for reasons discussed in Section 5.1. In this appendix, we consider alternative transformations that also accommodate exits post event. Estimates using these alternative measures are shown in Tables E1 and E2. An earlier version of this paper had used the ihs transformation to accommodate both continuing and exiting businesses in the outcome measure. However, as discussed in the main text, recent studies have raised questions about the interpretation of using the ihs transformation for the dependent variable.

We provide comparisons here to ihs results for background purposes. While appropriate caution is needed in interpreting the magnitude of such results, we think it is instructive to include these comparisons especially since relevant papers such as Becker and Hvide (2022) use this transformation. We also include a transformation related to that used by Smith et al. (2019). The latter paper uses as the profits per pre-event average employment. The analogue we consider in this comparison is the post-event revenue per employment in the event-year (where the latter is by sample restriction positive). We also include in this section a comparison of log based outcomes with those using TVV/DHS but restricting the latter to the cases where the log results are available (Table E2).

We find that the results using the TVV/DHS transformation which are scale-independent are broadly consistent with those using the ihs transformation which is not. However, there are non-trivial differences in magnitudes. Examining revenue per employment in the event

[4]Note that, unlike Nelson (2016) and Hyatt, Murray and Sandusky (2021), Azoulay et al. (2020) is based on employer startups in the LBD.

year yields significant declines in both real dollar terms and in a scaled version of this outcome. This holds for the full and log samples where outcomes are restricted to survivors. Finally, we show that the TVV/DHS transformation yields very similar results to those from the log transformation for the log sample (compare to Table 3 in the main paper) which is consistent with the TVV/DHS transformation being a close approximation to the log transformation.

Table E1: Alternative Transformations, Full Sample

	$dhs(emp)$	$dhs(rev)$	$ihs(emp)$	$ihs(rev)$	$\frac{rev}{emp_{dth}}$	$\frac{rev}{emp_{dth}}$ Scaled
P × T	-.05881***	-.06125***	-.08331***	-.1265***	-15.14***	-.09102***
	(.009723)	(.01189)	(.01218)	(.02323)	(3.933)	(.02364)
P × T × F	-.2303***	-.275***	-.1742***	-.5479***	-22.7***	-.1365***
	(.01449)	(.01913)	(.01649)	(.03686)	(6.658)	(.04002)
R^2	.3908	.4146	.7161	.6024	.8211	.8211
N	316000	204000	316000	224000	227000	227000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. P, T, F are $Post$, $Treated$, and $Founder$ respectively. The final column is scaled by normalizing to the value to the death shock year. Full sample, inclusive of exits (zero activity).

Table E2: Alternative Transformations, *ln* Sample

	$dhs(emp)$	$dhs(rev)$	$ln(emp)$	$ln(rev)$	$\frac{rev}{emp_{dth}}$	$\frac{rev}{emp_{dth}}$ Scaled
P × T	-.03429***	-.0379***	-.03583***	-.05057***	-13.86***	-.08328***
	(.008182)	(.009725)	(.009717)	(.01207)	(3.768)	(.02264)
P × T × F	-.02922**	-.1115***	-.03397**	-.126***	-9.238	-.05552
	(.01169)	(.01477)	(.01362)	(.01829)	(6.539)	(.0393)
R^2	.5233	.5116	.8767	.8918	.8437	.8437
N	293000	194000	290000	210000	215000	215000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. P, T, F are $Post$, $Treated$, and $Founder$ respectively. The final column is scaled by normalizing to the value to the death shock year. *ln* sample, excludes exits (zero activity).

F Founder Definition and Prior Earnings

As an alternative to a dichotomous distinction between founders and early joiners, we leverage the granular prior earnings profile of each member. An individual's level of earnings is likely positively related to holding key leadership positions in the firm. We measure each individual's most recent earnings before joining the startup. We examine whether losing a high-prior earnings initial team member is especially detrimental to startup performance. To focus on within-firm variation in prior earnings, we measure the extent to which a initial team's average prior earnings changes following the loss of a member.[5][6]

In Table F1, we show interaction effects with the relative prior earnings variable. The loss of a initial team member with average prior earnings among the initial team yields large and statistically significant reductions in employment and revenue. For example, the impact of losing an initial team member with average prior earnings, inclusive of exit, is roughly 14% for both employment and revenue. These effects fall between the early joiner and founder estimates in Table 3. Moreover, the impact of losing an initial team member generally increases with the level of the member's prior earnings. This pattern is consistent with our previous finding that losing an early joiner has a meaningful but yet less consequential effect compared to losing a founder. Therefore, these results based on prior earnings provide additional support to the idea that initial team members are important and that their relative importance significantly varies within the team.

Table F1: Prior Earnings Heterogeneous Effects

	dhs(emp)	*dhs(rev)*	*log(emp)*	*log(rev)*
Post × Treated	-.1481***	-.1557***	-.04482***	-.08924***
	(.008206)	(.01042)	(.007754)	(.01011)
Post × Treated × Prior Earn	-.2037***	-.311***	-.0357	-.1757**
	(.04615)	(.06338)	(.04191)	(.0597)
R^2	.3943	.4197	.8775	.89
N	243000	163000	223000	166000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Regressions specifications also include *Post* and *Post* × *PE*, the estimates for which are excluded for simplicity.

[5]Specifically, $PR_i = \frac{1}{N_i}(pr_i - PR_i^{FT})$, where N_i is the number of active initial team members at the firm in the quarter before the death shock, PR_i^{FT} is the average prior earnings of those members, and hc_i is the prior earnings of the deceased member. Because pr_i and PR_i^{FT} are measured in logs, PR_i measures the percentage change in the average prior earnings of the remaining initial team caused by the death shock.

[6]This relative change measure has similar properties to a term in the decomposition method developed by Foster, Haltiwanger and Krizan (2001), who break down the change in aggregate productivity into the components driven by entrants, stayers, and exiters. A initial team member death is analogous to an exit that causes a change in the average prior earnings of the remaining initial team members.

G Death Shocks and Anticipation Effects

To ensure that a initial team member death is unanticipated, we follow the literature and define premature death as occurring at an age less than 60. Even so, one might question whether these deaths are truly unanticipated. For example, a critical health condition of a founder might be known years before their death, allowing the firm to adjust to such news in advance. We address this concern in our baseline sample by restricting to cases in which the deceased individuals are active wage earners at the firm in the same quarter the death is observed. Moreover, parallel pre-trends demonstrate that there is no statistically identifiable anticipation effect.

Nonetheless, we test whether our results differ when the death occurs among relatively younger individuals, for whom death is likely to be more difficult to anticipate. We classify treated firms based upon whether the initial team member that died was above or below the median age of all initial team deaths in our sample.[7] Table G1 shows the effects interacted with whether the deceased initial member is relatively older. We find no difference in the effects of deaths of young versus old founders or early joiners members. Similar results in both the direction and magnitudes for young versus old individuals allay the concerns about anticipation effects and the exogeneity of our death shock.

Table G1: Older Initial Team Member Deaths

	dhs(emp)	*dhs(rev)*
Post × Treated	-.06333***	-.07815***
	(.01374)	(.01676)
Post × Treated × Founder	-.2223***	-.2648***
	(.02211)	(.02912)
Post × Treated × Old FT	.008796	.03304
	(.01945)	(.02378)
Post × Treated × Old FT × Founder	-.01449	-.02305
	(.02942)	(.03871)
R^2	.3909	.4148
N	316000	204000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information. Regressions specifications also include *Post* and *Post* × *Old FT*, the estimates for which are excluded for simplicity. *Old FT* is equal to 1 if the founding team member that died was above the median age (45 years old) of all founding team member deaths.

[7]The median age of initial team members who died in our sample is 45 years old.

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