Early Joiners and Startup Performance*

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Abstract

We show that early joiners—non-founder employees in the first year of a startup—play a critical role in shaping firm performance. We use administrative employer-employee matched data on US startups and utilize premature death as a natural experiment that exogenously separates talent from startups. We find that losing an early joiner has large negative effects on employment and revenues that persist for at least ten years. In contrast, losing a later joiner yields only a small and temporary decline in firm performance. Our results imply that organization capital, an important driver of startup success, is embodied in early joiners.

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1 Introduction

Why do most startups fail in their first five years while a small share go on to experience outsized growth and success (Decker et al., 2014; Pugsley et al., 2021)? One important source of the extreme skewness in startups' performance may be their initial endowment of human capital embodied in the founding entrepreneur (Lucas, 1978; Lazear, 2004). Evidence has accumulated in support of the critical role of founders in setting the initial vision and shaping the growth and performance of their ventures (Kaplan et al., 2009; Agarwal et al., 2020; Smith et al., 2019; Becker and Hvide, 2022).[1]

While the focus on founders is sensible, these individuals often account for only a handful of people among the initial team of employees at a startup. In this paper, we widen the focus to the entire initial team and decompose the team into founders and early joiners. Our definition of founders is inclusive of owners and selected top personnel. Early joiners, in contrast, are the remaining employees in the first year of operations. Little is known about whether or how such early joiners contribute to the success of young firms. On the one hand, early joiners may have little to no impact on startup performance if their primary contribution is readily-substitutable human capital. On the other hand, early joiners may be a vital ingredient to firm success, contributing to the organization capital that distinguishes a new firm. By organization capital, we mean the company-specific norms, routines, business practices, and tacit knowledge that differentiate firms (e.g. Prescott and Visscher, 1980; Nelson and Winter, 2002; Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013).

As motivation, consider the case of Marissa Mayer, who joined Google in 1999 shortly after its founding. Mayer initially joined as a junior programmer but her role quickly expanded. She soon became the lead architect of the landing page of Google's website, shaping the experience of every user of Google's search engine. Though she later left the firm in 2012 to become the CEO of Yahoo, Mayer's legacy at Google continues to persist as her pioneer-

[1]More generally, leaders of firms such as CEOs are known to be important for the growth and well-being of their organizations e.g., Bertrand and Schoar (2003); Jones and Olken (2005); Bloom et al. (2013).

ing work on Google's first homepage and advertising-based revenue model helped lay the foundations of the company's success.[2]

We study the contribution of early joiners, such as Marissa Mayer, and initial teams more broadly, to the survival and growth of startups. We begin with an illustrative model, which provides intuition for why the initial team (i.e., both founders and early joiners) might impact the long-term trajectory of new firms. We posit that in the nascent stages of new businesses, initial team members generate organization capital that becomes embodied in, and thus inalienable from, the team members themselves (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013). They are therefore not easily replaceable with outside individuals and losing an initial team member can result in the loss of accumulated organization capital.

We test these ideas leveraging employee-employer matched data from the US Census covering all startups with paid employees established between 1990 and 2015. Initial teams are identified as all individuals with positive earnings in the first year of operation, supplemented by owners of sole proprietorship firms whose identities are obtained from income tax filings. Our focus is on startups that organize themselves as sole proprietorship or corporation, as we can measure initial teams in a consistent manner; we exclude partnerships because their business owners are prohibited from receiving wages and thus do not appear in our database. In contrast, active owners of corporations are required by law to be paid employees.

Founders are defined to be the top three employee earners in the first year for corporations and the owner plus the top two employee earners for sole proprietors. Founders are also required to be present on "day one." Evidence shows that for employer corporations, the vast majority of owners with nonzero salaries are among the top three earners (Azoulay et al., 2020). This inclusive definition of founders permits us to define early joiners as the remaining employees present in the first year of operations. These definitions imply that

[2] We focus on the role of early joiners in the outcomes over the first ten years after founding. An open question we leave for future research is the evolution and embodiment of organization capital in more mature firms.

early joiners are very unlikely to include business owners. As an alternative to decomposing the initial team in this manner, we also use each initial team member's most recent earnings before joining the startup as a proxy for their human capital.

We begin by providing a series of stylized facts that demonstrate the correlation between the attributes of initial team members, both founders and early joiners, and startup outcomes. Startups launched by initial teams with higher prior earnings, among both founders and early joiners, are more likely to survive and grow in both employment and revenue, and tend to have higher labor productivity. These patterns provide a rich portrait of young firm heterogeneity suggesting the importance of initial teams. Nonetheless, a number of endogeneity issues complicate the causal link between initial team characteristics and firm outcomes. High-ability individuals may be more likely to associate with ventures based on ideas or technology with greater market potential. The positive relationship between the initial team's prior earnings and firm outcomes, therefore, could reflect unobserved characteristics, such as the quality of the underlying business idea, that are endogenously tied to the characteristics of the initial team.

To identify a causal relationship between initial team members and startup performance, we exploit a natural experiment that exogenously separates talent from the startups—specifically, premature death. In a difference-in-differences framework, we compare roughly 25,000 startups that experience a premature death of an initial team member to a closely matched group of "twin" startups that do not. We examine firm outcomes such as employment and revenue as well as survival of the firms, and keep track of them for several years to see how quickly the firms recover from disruptions caused by the shock. We also leverage the large scale of our data and conduct heterogeneous treatment effects analyses to investigate the mechanism behind the results.

Our main finding is that early joiners play a critical role in determining startup success and losing them leaves a near-permanent scar on firm performance. Our estimates indicate that losing an early joiner lowers both employment and revenue by roughly 6%. These negative effects do not dissipate even 10 years after the shock, implying that disruptions caused by the loss of an early joiner are not resolved by replacement hiring. Consistent with prior studies using different data and in different settings, we find that losing a founder yields qualitatively similar and larger effects (e.g. Smith et al., 2019; Becker and Hvide, 2022). We use founder effects as a benchmark for interpreting the magnitude of early joiner effects. Losing a founder or early joiner lowers the likelihood of firm survival. However, the extensive margin effect is especially large for a founder and the impact is almost immediate; the likelihood of survival declines substantially after the first year of losing a founder but declines no further over the next five years. In contrast, the loss of an early joiner has almost the same adverse impact on employment, though not necessarily on revenues, as the loss of a founder in terms of both magnitude and persistence. In other words, losing an early joiner is more important on the intensive than the extensive margin. We also find that the relative importance of early joiners increases with the age of firms.

To provide perspective on why early joiners matter, we explore a number of heterogeneous treatment effects in settings in which the importance of organization capital from early joiners is expected to be amplified or attenuated. For example, Delgado and Mills (2020) provide persuasive evidence that organization capital is especially important for business-to-business (B2B) oriented firms. B2B firms produce specialized inputs and their success depends on complex downstream B2B relationships. We find that the gap in the adverse impact of an initial team member loss between early joiners and founders narrows in B2B industries, suggesting that early joiners are relatively more important in those industries. We also explore the differential impact of founders versus early joiners on startups by initial team size, as each team member would possess a greater share of organization capital in relatively small teams, and we confirm that early joiners are relatively more important in smaller teams. Moreover, we compare the effects between corporations and sole proprietorships based the idea that organization capital in corporations is more broadly shared beyond business owners and corporations are more growth-oriented (Guzman and Stern, 2015). We find that early joiners are relative more important in corporations. In addition, we assess the heterogeneous effects with respect to various measures of skill intensity of the industries and find that early joiners matter more in industries where general skills are more intensely utilized.

Two robustness analyses help demonstrate the importance of early joiners. First, we examine the loss of second-year joiners, employees hired in the second year after startup. We find that there is a transitory adverse impact on the firm that is reversed within two to three years after losing the second-year joiner. This finding is broadly consistent with Jäger and Heining (2022) who find that the loss of an employee at a small business leads to a modest but temporary reduction in the firm's growth. In contrast, the loss of an early joiner has an adverse effect that persists for at least 10 years. Second, we consider an alternative approach to differentiating individuals within the initial team. Instead of decomposing the initial team into founders and early joiners, we characterize individuals based on their earnings prior to joining the startup. As expected, we find that the loss of an initial team member with higher relative prior earnings has a larger adverse impact. Importantly, however, the loss of an initial team member at the average of the within-firm prior earnings distribution also has a significant adverse impact. This suggests that the average initial team members who are most likely to be early joiners are critical for firm performance.

The paper is organized as follows. In Section 2 we discuss the related literature and a conceptual framework that describes how organization capital developed by a initial team relates to standard models of firm dynamics. We then discuss our data infrastructure in Section 3. Section 4 describes basic facts about the post-entry dynamics of startups and the relationship of these dynamics to the characteristics of initial teams. Section 5 presents our identification methodology using premature deaths, our main results, and then analysis of heterogeneous treatment effects. Section 6 concludes.

2 Background

Related Literature

Organization capital consists of company-specific norms, culture, business practices, and tacit knowledge that differentiate firms (e.g. Prescott and Visscher, 1980; Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013). This concept is especially salient in the context of entrepreneurship for two reasons. First, prior studies posit that the core components of organization capital are developed in the early years of the firm (Nelson and Winter, 2002; Campbell, 1998). Second, the prevailing view in this literature is that organization capital becomes embodied in the firm's key talent such as founders (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013). We build on this work by investigating whether early joiners—who are also present in the early stages of the firm—contribute to the development of their employers' organization capital. As such, we focus on whether organization capital becomes embodied in the early joiners alongside the founders.

Our work builds on two recent studies that use a similar identification strategy to quantity the contribution of founders to firm performance. Smith et al. (2019) find large and persistent negative effects on pass-through profit from premature deaths of business owners. They use data for the US from the IRS to focus on pass-through businesses held by individuals at the top of income distribution. Many of these firms are legacy businesses passed down from parents to their children. Our study, in contrast, focuses exclusively on young firms. The second related study by Becker and Hvide (2022) investigates the impact of premature deaths of founders on startups using Norwegian administrative data. They find large, adverse, and persistent impacts of losing founders on various firm outcomes. While our findings on founders are broadly consistent with this study, we provide findings on founders for a much larger sample of US young firms.

Our primary contribution, closely related to this literature, is to broaden the focus to the entire initial team and demonstrate the significance of early joiners for startup performance.

Our findings show that early joiners are not as important as founders to firm performance, but still play a critical role above and beyond that of rank and file employees as in Jäger and Heining (2022). We also find that early joiners matter in a different way than founders. Early joiners are relatively more important on the intensive margin and as the firm ages.

We are not the first to hypothesize that early joiners may play a role in shaping the trajectory of startups. Several recent studies examine issues such as early joiners' wages, preferences for joining startups, and enduring impact on how tasks are performed (Roach and Sauermann, 2015; Burton and Beckman, 2007; Kim, 2018; Sorenson et al., 2021). Our findings complement these studies by providing causal evidence that losing an early joiner in a startup can lead to a large persistent drop in firm performance, while this effect disappears when losing a later joiner.

Our work also contributes to the entrepreneurship literature by exploring initial team characteristics as an important determinant of startup growth. The prior literature has identified a number of initial characteristics that correlate with firm outcomes, including the age of the workers (Ouimet and Zarutskie, 2014), the outside options for and age of the founders (Choi, 2017; Azoulay et al., 2020), and the name or the incorporation location of the business (Guzman and Stern, 2015). Our findings highlight the importance of taking into account the contributions of early joiners.

Our work also builds upon the firm dynamics literature. Several studies have stressed that high-growth young firms play a disproportionate role in job creation and productivity growth (Decker et al., 2014; Alon et al., 2018). Canonical models of firm dynamics attribute growth heterogeneity to initially drawn productivity or demand (Jovanovic, 1982) and post-entry shocks (Hopenhayn and Rogerson, 1993). There is growing evidence that the initial differences—or ex-ante heterogeneity—play a critical role (Pugsley et al., 2021), and we contribute to the literature by identifying initial teams as a salient initial firm characteristic. The simple conceptual framework we discuss in the next section helps make the connection to this literature.

Conceptual Framework

In a standard model of entry, selection, and growth (Lucas, 1978; Hopenhayn, 1992), entrants pay a fixed cost of entry, learn their productivity draw, and then face a profit function with curvature (from either decreasing returns or product differentiation) and a fixed cost of operation. Firms with high productivity draws become large, those with low draws stay small, and those with sufficiently low draws exit because of their inability to cover fixed costs. Permitting dynamic learning or other adjustment frictions enables interesting post-entry dynamics (Jovanovic, 1982; Hopenhayn and Rogerson, 1993; Ericson and Pakes, 1995).

We think a useful way to interpret the fixed cost of entry is that it reflects the time and resources required to invest in the organization capital that makes firms distinct. An illustrative model that formalizes this organization capital interpretation of the startup process is presented in Appendix C. We show how the initial team (including both founders and early joiners) of a business can play a critical role in the development and success of the investment in organization capital. Relatedly, we show how the standard assumption of an ex post productivity draw can be interpreted as a draw from a distribution of initial team match quality. Next, we provide an overview of the issues and implications of such a model, which helps motivate the empirical analysis that follows.

Several issues emerge in this interpretation of the business formation period of startup firms. First, do all initial team members contribute to the organization capital? A narrow view is that it is only the founders that contribute while a broader view is that all initial team members make important contributions. A second issue is the extent to which organization capital is embodied in the initial team. If the organization capital is inalienable, then the loss of an initial team member will have an adverse impact on firm performance. This negative impact is likely to manifest in multiple measures of performance, including the scale of operations in terms of revenue and employment and survival. In our empirical analysis, we examine the impact of the loss of both founders and early joiners on all of these outcomes.

3 Data Infrastructure

We construct a longitudinal data set covering the majority of startups and their initial teams established between 1990 and 2015 by combining data from the Longitudinal Business Database (LBD) and the Longitudinal Employer-Household Dynamics data (LEHD). The details of our data infrastructure are in Appendix D. We provide an overview here. The LBD permits us to track startups and their post entry performance in terms of revenue, employment and survival. The LEHD enables us to track those on the payroll at the firms.

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 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 Census Business Register (BR) which underlies the LBD. 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. In contrast, 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.[3]

While the existing entrepreneurship literature focuses almost exclusively on founders, we decompose the initial team into two groups: founders and early joiners.[4] 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

[3]Indeed, using K-1 and W-2 filings data, Nelson (2016) finds about 84% of all S corporations with paid employees have at least one shareholder employee.

[4]For a few exceptions studying non-founding employees of startups, see Ouimet and Zarutskie (2014), Coad et al. (2021), Roach and Sauermann (2015), Kim (2018), and Sorenson et al. (2021).

et al. (2020)). 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 of operations. 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. For our purposes, we are especially interested in the contribution of early joiners. It is very unlikely that business owners are classified as early joiners (see Appendix D for further discussion).

We use the prior earnings of each initial team member as a proxy for human capital, which captures heterogeneity in skills and experience. Prior earnings are computed as the individual's most recent full-quarter earnings before joining the startup.[5] An important feature of this approach is that prior earnings are an ex-ante characterization of each individual and therefore a useful proxy for human capital. Moreover, prior earnings serve as a robustness check to our definition of founders and early joiners (see Table F1 in Appendix F and accompanying discussion). In the following section, we establish some basic facts in the relationship between prior earnings of the initial team—separately for founders and early joiners—and firm outcomes.

Our dataset for basic facts, and the frame from which our causal analysis is drawn, tracks more than 6 million startups and over 72 million initial team members from 1990 to 2015. The database includes each LEHD state as the data become available in the LEHD infrastructure. State-level coverage in the LEHD varies over time but by 2000 coverage is

[5] Full-quarter earnings is measured as earnings for a quarter in which the individual also was observed with earnings in the previous and subsequent quarter. These restrictions ensure the earnings measure captures an entire quarter of work rather than a partial quarter. Earnings captures total compensation paid, including bonuses, stock options, severance pay, and profit distributions (Bureau of Labor Statistics, 2022).

nationally representative.

4 Basic Facts about Firm Outcomes and Initial Teams

Before exploring the relationship between founding team characteristics and firm performance, we first verify that our data infrastructure has properties consistent with the findings in the literature. Consistent with previous studies, we find that the exit rate of young firms is higher than older firms but that, conditional on survival, young firms have higher average growth rates than older firms. These results can be found in Figures B1, B2, and B3 in the Appendix.[6]

Turning to the characteristics of initial teams, we find systematic and statistically significant relationships between the prior earnings of initial teams and firm performance. We calculate the average prior earnings of founders and early joiners of each startup and organize the firms into 20 equal-sized bins by average prior earnings. Then we regress five-year employment and productivity growth rate outcomes and a binary indicator reflecting firm exit on the prior earnings bins, controlling for industry by year fixed effects and initial conditions (initial employment for survival and employment growth and initial productivity for productivity growth). We find that startups with high-prior earnings initial teams experience faster employment and productivity growth conditional on survival (panel (a) and (b) of Figure 1) and are less likely to exit (panel (c) of Figure 1). These patterns hold monotonically in all parts of the prior earnings distribution except for the very top for employment growth and exit outcomes.

Leveraging the longitudinal structure of our data, we also examine post-entry attrition patterns among founders and early joiners. We find that the average numbers of founders and early joiners remaining at the firms decline as firms age, while, interestingly, attrition among the initial team generally stems from the bottom of the prior earnings distribution. That

[6] In our basic facts analysis, productivity is measured as real revenue per worker. This measure is highly correlated with TFP when controlling for detailed industry and year effects (see Decker et al. (2020)).

is, conditional on survival, the average prior earnings of initial team members remaining at the startup increases over time. Finally, we also find evidence of substantial positive assortative matching between founders and early joiners; founders with high prior earnings tend to associate with early joiners with high prior earnings. These results can be found in Figures B4 and B5 in the Appendix.

In short, we find that the prior earnings of initial teams is closely linked to the up-or-out dynamics of young firms. However, we are unable to interpret these correlations as causal because both the composition and attrition of the initial team are not random.

5 Causal Impact of Founders and Early Joiners

To identify the causal contribution of initial team members we use the premature death of founders and early joiners to approximate an experiment in which an initial team member is randomly separated from a startup. Our research design combines a matching strategy with a difference-in-differences analysis. This approach allows us to estimate changes in firm performance for "treated" startups that experience the premature death of a founder or an early joiner relative to similar startups that did not. For each startup firm that is treated in quarter t, we find a similar control firm by matching on characteristics measured in the same quarter. To focus on early-stage startup dynamics, we first consider firms that are treated within the first six years of operation. We then track firm outcomes for five years after the event, allowing for the possibility that the firm exits. One strength of our research design is that we can empirically test whether the treated and control firms exhibit parallel trends in outcome variables before the death shock. If the pre-treatment trends are not parallel, premature death is not likely to be as good as randomly assigned between the treated and control firms.

We rely on the Census Bureau's Numerical Identification File (Census Numident) to identify the date of death for each individual in our data. As described by Finlay and

Genadek (2021), the Census Numident file contains full-population death data derived from the Social Security Administrations Numerical Identification file (SSA Numident), which the SSA connects for purposes of administrating the Social Security program. Following Jaravel et al. (2018) and a number of other studies that use premature death as a source of identification, we classify premature death as death at or before 60 years of age.[7] For an initial team member's death to be considered a shock to the firm, we require that the individual have positive earnings during the quarter in which the death is observed. For sole proprietor owners, for whom we do not observe quarterly earnings, we measure their death as a shock to the firm if the firm has non-zero employees in the death shock quarter and did not change its EIN since its inception.[8] Treated firms are those with only one premature death in the first six years after firm entry.

We use coarsened exact matching strategy to select a single control firm for each treated firm (Blackwell et al., 2009). We require that our treated and control firms have the same birth year, operate in the same detailed industry (four-digit NAICS), have the same legal form of organization and reside in the same state. Because a firm with more initial team members will have a higher probability of treatment as more individuals are at risk of premature death, we also match on the number of initial team members who are working at the firm in the death shock quarter. The probability of a firm experiencing the death of an initial member is also positively related to the age of its initial team. Therefore, we match on the average age of the active initial team members in the death shock quarter. Typically, more than one control firm will be matched to each treated firm after the coarsened exact matching procedure. Instead of using matching weights, we select a single control for each

[7] We do not observe the cause of death in these data. For examples of studies using premature deaths for identification purposes see Jones and Olken (2005); Nguyen and Nielsen (2010); Azoulay et al. (2010) and Oettl (2012). We show in appendix G that results are robust to using deaths of initial team members under 45.

[8] If a business experiences a change in ownership it must request a new EIN or file using different, already existing EIN.

treated firm, choosing the closest matched control firm based on the absolute differences in the continuous matching variables. Ties are broken randomly. Control firms are selected without replacement; we do not allow a firm to be used as a control for multiple treated firms.

Selected summary statistics for the treated and control firms, evaluated in the treatment (death shock) year, are presented in Table 1. The sample contains roughly 52,000 firms with an equal split between the treated and control groups.[9] The sample is reduced for revenue-based measures, as only about 80% of firms in the LBD are assigned revenue values. In terms of balance, treated and control groups have similar firm age, initial team age, and (log) levels of employment, revenue, and labor productivity.

5.1 Main Results

The primary outcome variables of interest are changes in the relative size of businesses in terms of employment and revenue, and survival of firms. For our primary analysis of employment and revenue outcomes, we use a simple relative change measure developed by Tornqvist et al. (1985) that has been actively used in the literature on firm dynamics for a measure of firm growth that accommodates entry and exit (Davis et al., 1996).[10] The measure we use in our setting is given by $\tilde{Y}_{i,j,t} = (Y_{i,j,t} - Y_{i,j,0})/(0.5(Y_{i,j,t} + Y_{i,j,0}))$ where $Y_{i,j,t}$ is revenue (employment) for startup i, in industry j, in year t and $Y_{i,j,0}$ is the revenue (employment) in the year of the death shock. We denote this measure TVV/DHS in what follows.

The TVV/DHS measure has several advantages. First, it is symmetric in terms of increases and decreases as is the log difference measure of relative change, and unlike the log difference, this measure accommodates zeros.[11] Second, the TVV/DHS measure is

[9] In unreported results, we find that this sample has similar characteristics to the full initial team database.

[10] In our application, we are exploring outcomes post-entry for young firms so accommodating entry is not relevant. Accommodating exit is highly relevant.

[11] The TVV/DHS measure is closely related to the standard measure of relative change (e.g., $(y-x)/x$)

consistent with the guidance of Chen and Roth (2023) and Mullahy and Norton (2022) who suggest using such relative change outcome measures that are not arbitrarily scale-dependent. The TVV/DHS measure is scale independent (i.e., it is not dependent on the units for measuring revenue or employment).[12] Lastly, the measure we use is readily interpretable in terms of changes in the outcomes of interest relative to the shock year.

To estimate the dynamic impact of a premature death shock of a founder or an early joiner on employment and revenue, we use a difference-in-differences specification with leads and lags as shown in Equation (1).

$$\tilde{Y}_{i,j,t} = \sum_{k=-5}^{5} \lambda_k d[k]_{i,t} + \sum_{k=-5}^{5} \delta_k d[k]_{i,t} \times TREAT_i + \alpha_i + age_{i,t} + \tau_{j,t} + \epsilon_{i,j,t} \quad (1)$$

$\tilde{Y}_{i,j,t}$ is the outcome for startup i in industry j in year t. $d[k]_{i,t}$ are a series of relative year dummies before and after the death shock. $TREAT_i$ is the treatment dummy that equals 1 if the startup experiences the death of a founder or an early joiner and zero otherwise. α_i, $age_{i,t}$, and $\tau_{j,t}$ are firm, firm age, and industry by year fixed effects.[13] Estimates of δ_k

but the latter is not symmetric in terms of increases and decreases (Tornqvist et al., 1985). The TVV/DHS closely approximates the log relative change measure for positive outcomes as discussed in Davis et al. (1996) and Vartia (1976).

[12]An earlier version of this paper used the the inverse hyperbolic sine (ihs) transformation, which has been commonly used in the literature including, for example, by Becker and Hvide (2022). Potential issues of scale dependency using the ihs transformation has been discussed in the literature and guidance about these issues has been provided in papers such as Bellemare and Wichman (2020). However, the recent papers (e.g. Chen and Roth, 2023; Mullahy and Norton, 2022) raise serious concerns about the use of ihs even in light of that guidance. We provide further discussion of these issues in Appendix E, including a comparison of our TVV/DHS results with the ihs results and other transformations.

[13]To address other potential concerns such as the impact of firm-industry lifecycles, we employ industry $\times$ firm age fixed effects, as well as industry $\times$ firm age $\times$ year fixed effects, in alternative specifications and find consistent results. See Tables A2 and A3 in the Appendix. Moreover, qualitative and quantitative patterns for heterogeneous treatment effect regressions are robust to these different combinations of fixed effects.

are the parameters of interest, representing the change in outcomes in each year for treated firms relative to the control group. It is important to note that our sample is an unbalanced panel for two reasons. First, we do not condition on survival and keep only the year after firm death in the sample with zero economic activity (i.e., right truncation). Second, the death shock can occur early in the life of the firm (i.e., left truncation).

Figure 2 displays the effect of losing a founder and that of losing an early joiner on employment (panel a) and revenue (panel b). We find that the effects are large, negative and statistically significant for both the death of a founder and that of an early joiner. For example, losing an early joiner causes the employment and revenue to decline immediately after the shock by about 8%.[14] The negative effects are highly persistent as they last at least for five years after the death shock, indicating that the disruptions caused by the shocks are not easily resolved by hiring a replacement for the deceased individual. The death of a founder or an early joiner leaves a near-permanent scar on the firm's growth potential.[15] We also find that the adverse impact is larger for revenue than for employment, particularly following the death of a founder.[16] We do not find evidence of differential pre-trends for any of the outcome variables, lending credibility to our research design utilizing premature death shocks.

While the adverse effects on employment and revenue are substantially larger for a founder

[14]We convert the TVV/DHS based estimates to implied percent differences using the relationship between the TVV/DHS measure of relative change and the standard measure of percent changes. For any given x and y, the latter is $G = (x-y)/y$ and the former is $g = (x-y)/(0.5(x+y))$. The relationship between the two measures is given by $G = 2g/(2-g)$. For log based outcomes we use the standard $exp(log(y/x))-1 = (x-y)/y$ conversion of log differences to percent differences.

[15]Exiting firms are included in the sample in the firm death year with zero employment and those firms are dropped from the sample afterward, so that a firm's exit does not contribute to the estimation of the extensive margin effect multiple times.

[16]We estimate Equation (1) using the difference in the TVV/DHS measures for revenue and employment as the outcome variable to confirm that the larger effect on revenue is statistically significant for founders. The results are presented in Figure B6 in the Appendix.

than for an early joiner, especially in the first year after the shock, we find that much of this difference is due to extensive margin effects. We use a linear probability model to measure the impact of losing a founder or an early joiner on the likelihood the firm exits. As Table 2 shows, treated firms are roughly 26% more likely to exit within one year of losing a founder (panel a), while the corresponding effect for losing an early joiner is only 2% (panel b). The estimates for two to five years after the initial team member death remain statistically significant and remarkably stable. Five years after losing a founder, treated firms are 24% more likely to exit. These results suggest that the loss of a founder yields a significant negative impact at the extensive margin immediately after the founder's death.[17]

We also estimate the specifications using $log(employment)$ and $log(revenues)$ as dependent variables. These measures, by construction, condition on survival.[18] Results are presented in Figure 3. The patterns for the log-based outcomes are similar qualitatively to those for the TVV/DHS-based outcomes but they are distinctive in two ways. First, the gap between the estimated effects for a founder and an early joiner is noticeably narrower for log-based outcomes, especially for employment. Second, we no longer find the sharp decline in the first year followed by a slight recovery afterwards for log-based outcomes. These results are consistent with our finding that much of the differences in TVV/DHS-based outcomes between founders and early joiners is driven by the large effect on firm exit in the first year after the death of a founder. Overall, the adverse effects on log-based outcomes are less severe relative the TVV/DHS-based outcomes in Figures 2 as they only contain intensive margin effects, but they are still quantitatively large and persistent. $log(employment)$ declines by about 7% and 9% five years following the death shock of an early joiner and a founder, respectively.[19]

[17]As shown in Figure B7 in the Appendix, we find similar results when using a Cox proportional hazard model in which pool founder and early joiner deaths.

[18]Note that by construction treated and control firms exist at the time of the shock. No exit occurs before the death shock among either treated or control firms.

[19]For completeness, we also estimate the specifications using TVV/DHS for the samples that condition on survival. As shown in Table E2 in the Appendix, we find similar negative, albeit attenuated, effects

The *log* results potentially suffer from selection bias due to conditioning on positive activity in the post-treatment years. Treated firms that survived after being hit by the death shock may be more resilient than surviving control firms that did not experience such a shock. In that case, treated firms might have grown faster, on average, than their control counterparts in the absence of the shock, and thus negative effects on log outcomes could be attenuated. If the difference between treated and controls is quantitatively negligible, then selection bias is not a concern. While it is impossible to isolate how much faster or slower surviving treated firms would have grown compared to their control counterpart, we can characterize pre-treatment differences. First, the absence of pre-treatment differences in the event study estimates shown in Figure 3 provides evidence that selection bias is not a substantial concern. Second, we directly compare the growth rate of employment, revenue, and revenue per worker from birth to the year before the death shock year between the treated and control firms *conditional on surviving* after treatment. The results, shown in Appendix Table A1, show that growth patterns of treated and control firms that survived after treatment are indistinguishable.[20] Taken together, these results suggest that the selection bias in the estimated effects of *log* outcomes is small.

A striking feature of the *log* results is that the loss of an early joiner has almost the same adverse impact on employment, though not necessarily on revenues, as the loss of a founder in both magnitude and persistence. This pattern alleviates concerns about results being driven by misclassification of owners between founders and early joiners. For sole proprietors, there is no chance of misclassification as the information from owners derives from income tax returns filed by owners. For corporations, using the evidence from Nelson (2016) and Azoulay et al. (2020), a back-of-the-envelope calculation suggests the probability that the founders include an owner is 76% while the probability that early joiners include an owner is 8%.[21] This nine-fold difference is much larger than the difference in the impact

associated with the loss of both early joiners and founders.

[20]For simplicity, we combine founder and an early joiner premature deaths in this analysis.

[21]Nelson (2016) finds that 84% of S corporations with paid employees have at least one employee owner,

for either the TVV/DHS or the *log* results – and especially for the *log* results.

To summarize the main results and estimate the differences in the effects of founders and early joiners, we collapse the leads and lags into a binary pre/post treatment indicator and introduce a founder dummy variable to the regression specification as in Equation (2).

$$\begin{aligned}\tilde{Y}_{i,j,t} =& \lambda \cdot POST_{i,t} + \delta \cdot POST_{i,t} \times TREAT_i \\ &+ \beta \cdot POST_{i,t} \times TREAT_i \times FOUNDER_i \\ &+ \eta \cdot POST_{i,t} \times FOUNDER_i + \alpha_i + \tau_{j,t} + \gamma_{i,t} + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

$\tilde{Y}_{i,j,t}$ is the outcome for startup i in industry j in year t. $POST_{i,t}$ is the time dummy that equals 1 if $0 \leq t \leq 5$ and 0 otherwise, with $t = 0$ being the death shock year. $TREAT_i$, α_i, $\gamma_{i,t}$, and $\tau_{j,t}$ are identically defined as in Equation (1). δ is the treatment effect when the deceased member is an early joiner ($FOUNDER_i = 0$) and β captures the additional effect when the deceased individual is a founder ($FOUNDER_i = 1$).[22] For brevity, we only report the estimates for δ and β.

The first two columns in Table 3 display the estimation results of Equation (2) using TVV/DHS and *log*-based employment and revenue outcomes. As in the event study figures, the table shows that losing a founder has a larger impact than losing an early joiner and the differences are statistically significant. The additional negative effect for founders is roughly four times as large for employment and even larger for revenue using TVV/DHS. Nonetheless, we find that losing an early joiner results in a significant and negative impact on both measures of firm performance. The death of an early joiner causes both employment and revenue to decline by 6% over the subsequent five years. The last two columns of Table

and Azoulay et al. (2020) find that conditional on the presence of an owner among employees, 90% are among the top three earners.

[22]For these analyses we do not include $FOUNDER_i$ as a separate control because it is not identified with the inclusion of firm fixed effects.

3 show the *log*-based outcomes, which as before condition on survival, capturing intensive margin effects. Consistent with Figure 3, we find that the negative impact for losing a founder is larger and statistically significant, the gap is smaller than for TVV/DHS-based measures, and the difference is larger for revenue than for employment. Conditional on survival, losing an early joiner reduces employment by 3.5% while losing a founder decreases employment by 6.9%. These estimates highlight that it is not only founders, but also early joiners who meaningfully contribute to startup growth and survival. Interestingly, the impact of early joiners mostly operates at the intensive margin in contrast to that of founders.

5.2 The Relative Importance of Initial Team Members

Next, we explore whether the importance of an early joiner or founder varies systematically depending on firm and initial team characteristics. The first question we explore is whether losing an early joiner compared to a founder varies as a firm ages. Here we are motivated by the example of Marissa Mayer who became a vital contributor after a few years at Google. More generally, this section centers around the role organization capital plays in explaining the decline in startup performance following the loss of an initial team member. We revisit our theory of organization capital, which we define as the tacit knowledge and resources developed in the nascent stages of a venture. If at least some organization capital is embodied in individuals, it is (partly) lost when an initial team member separates from the firm. The impact of losing such embodied organization capital will depend on the context-specific salience of organization capital. For instance, a sudden loss of organization capital can be less detrimental for startups that operate on knowledge more easily codified and communicated and thus more easily transferred from the initial team members. We test this empirically by examining settings in which the role of organization capital is expected to be amplified or attenuated. For the analysis, we extend our regression Equation (2) by further interacting the independent variables with the dimension of heterogeneity of interest.

5.2.1 Young versus Mature Firms

In the early phase of their life cycle, young firms learn about the viability of their business ideas (Jovanovic, 1982; Kerr et al., 2014) and build a customer base from the ground up (Foster et al., 2016), often in the face of financial constraints (Schmalz et al., 2017). Because young firms are underdeveloped along many dimensions, they can be especially sensitive to unanticipated shocks relative to more mature firms (Fort et al., 2013). As such, we might expect the impact of losing both early joiners and founders to decline as the firm matures. Alternatively, if the organization capital embodied in initial team members becomes reinforced over time, then we might expect that losing an early joiner or founder later in the firm's life cycle would have a larger negative impact on firm success. The example of Marissa Mayer at Google highlights that it took some time for her contribution to become critical to the firm. To investigate these possibilities, we extend our data to cover initial team member deaths that occur when the firms are older (up to age 11). We explore heterogeneous treatment effects of the early joiner and founder death shock by maturity of the firms, comparing firms between age 0 and 5 to those age 6 and 11.

The results, presented in Table 4, show that the effects of losing an early joiner over the firms life cycle are different than for losing a founder. The negative impact of losing an early joiner rises as the firm matures while the impact of founders is more stable. The negative effect on employment of losing an early joiner is 6% for young firms and 10% for mature firms. The employment effect of losing a founder, in contrast, is a 25% decline for young firms and a 24% decline for mature firms. Revenue effects exhibit similar patterns. Losing an early joiner results in a 6% and 10% decline for young and mature firms respectively and 29% and 28% for founders.

The large and immediate extensive margin effect of losing a founder, shown in Table 2, is consistent with the idea that startups are particularly vulnerable in their earlier stages. The stability of the founder-death effect over the firm's life cycle, however, suggests that even as the firm matures, and ideas become codified, founders' impact on firm performance remains similarly important. Moreover, this stability also suggests that our main results are not primarily driven by the inherent sensitivity of nascent firms—even mature firms that lose a founder experience significant declines in performance.

Losing an early joiner, in contrast, has a larger impact on mature firms. This is consistent with the idea that the importance of early joiner's organization capital grows over time as these individuals' routines and imprinting effects become more integrated into the firm. One interpretation of the stable founder-effects and increasingly negative early joiner-effects is that the timing of their contribution to organization capital operates differently. While a founder's contribution might be substantial and materialize at firm birth, early joiners' impact may accumulate over time.

The increasing impact of early joiners over time is also consistent with the attrition dynamics shown in Appendix Figure B4. Early joiners that remain at the firm until it is mature tend to have higher prior earnings. The rising prior earnings of stayers is also apparent among founders, which suggests that composition effects alone cannot explain the differences we observe in the effects of early joiners and founders over the firm's life cycle.

5.2.2 B2B- versus B2C-intensive Sectors

Next, we explore whether the impact of losing an early joiner or a founder is greater for business-facing (B2B) rather than consumer-facing (B2C) startups. Delgado and Mills (2020) describe how B2B firms are likely to depend more heavily on relationships with specific downstream customers. Goods and services for such firms have a greater degree of specificity. Consequently, a greater share of the organization capital is likely embedded in the initial teams of B2B businesses due to the specificity of goods, services, and customer relationships.

We test this by comparing startups in B2B- and B2C-intensive industries. While we cannot make this categorization at the firm level, we rely on input-output accounts data from the U.S. Bureau of Economic Analysis to characterize each industry at the six-digit NAICS level. Following Delgado and Mills (2020), we categorize an industry as B2B-oriented if more than 66% of the total sales in the industry are to businesses or the government rather than to personal consumption, and B2C otherwise.[23]

Consistent with our theory of organization capital, the third and fourth columns in Table 4 show that losing an early joiner or a founder in a B2B-intensive sector leads to a greater decline in startup performance than in a B2C sector. The estimates are significant and the economic magnitudes are large. The additional negative impact of losing an early joiner in a B2B industries is roughly 4% for employment and 5% for revenue. Relative to the baseline effect among B2C-intensive sectors, these estimates represent 106% and 116% larger effects on employment and revenue, respectively. To evaluate the effects for a founder in B2B versus B2C industries, we compare the sum of the coefficients in all four rows with those in the first two rows. Relative to the baseline effect of losing a founder among B2C-intensive sectors, the results indicate an increase of 19% and 40% in negative effects on employment and revenue, respectively. These findings are consistent with the view that the importance of relationships in B2B businesses amplifies the role of the initial team, and the relative importance of early joiners in B2B-intensive industries is larger than that of founders.

5.2.3 Small versus Large Initial Teams

We also examine whether the negative impact of losing an initial team member is larger for startups with small initial teams. Intuitively, each initial team member would possess a greater share of organization capital in relatively small teams. Therefore, we expect the impact of an initial team member death shock to be larger for smaller teams. For this purpose, we define small teams as those with five or fewer active team members in the year before the death shock.

The fifth and sixth columns in Table 4 present the results based on team size. Consistent with our organization capital hypothesis, we find that losing a founder or an early joiner

[23] The distribution of sales to businesses versus consumers across industries is highly bimodal, making a binary categorization appropriate. Nonetheless, results are robust to using a continuous measure of B2B orientation.

leads to a larger negative impact for small teams. The additional treatment effect associated with losing an early joiner in small teams for employment is almost three times as large as the baseline effect among larger teams. The impact for revenue exhibits a smaller but nonetheless significant difference. These estimates again support the view that the main effects are driven by the loss of organization capital associated with the lost initial team member, which will be greater among smaller teams.

5.2.4 Corporations versus Sole Proprietors

Next, we examine whether the relative importance of early joiners and founders varies depending on whether the firm is a corporation or a sole proprietor business based on the idea that organization capital in corporations is more broadly shared and corporations are more growth-oriented (Guzman and Stern, 2015). Estimates comparing effects for corporations and non-corporations (sole proprietorships) are shown in the final two columns of Table 4. Indeed, we find that the effect of losing an early joiner is substantially more detrimental for corporations than for sole proprietor firms. Losing an early joiner in a corporation lowers employment by 7% while this negative effect no longer holds for sole proprietors. Similar countervailing effect is found for revenue. In contrast, the effect of losing a founder is larger in sole proprietorship firms than in corporations. These results are consistent with the view that organization capital embodied within early joiners is more salient for corporations.

5.2.5 Skill Intensity

Lastly, we examine whether the negative impact of losing an early joiner is related to their skills. We exploit several measures of skill intensity, starting from the share of workers in each industry with a bachelor's degree—a general measure of human capital—to more specific measures such as the share of employment in STEM occupations, which is often used to classify industries as High Tech.[24] The latter approach is motivated by our example of Marissa Mayer at Google, which raises the question as to whether the role of initial teams and early joiners is especially important for startups in innovative, growth-oriented ventures such as those in High Tech industries. We also exploit the employment share of abstract-intensive occupations, motivated by the idea that workers in these occupations are not easily substitutable with automation technologies (Autor and Dorn, 2013). Finally, we test whether the effects are stronger when losing an early joiner or founder with prior work experience in a related industry.[25]

First two columns of Table 5 show the results based on the share of college graduates in the start-up's industry. We find that losing an early joiner is particularly damaging in more college worker-intensive industries. A 10 percentage point increase in the share of college graduates raises the negative impact on employment and revenue by 1.7 and 1.6 percentage points, respectively. In contrast, as shown in the next four columns, we do not find any evidence that the effects differ between High Tech and non-High Tech industries or in industries with more or less employment in abstract-intensive occupations. These results indicate that the importance of early joiners varies with more general measures of skill (e.g. college share) but does not vary based upon STEM or abstract-intensive occupation intensities.

We also test whether the negative effects are stronger when the lost early joiner or founder had experience in an industry that is closely related to the startup's industry. We measure industry-relevant experience using an index of cross-industry job-to-job flows developed by

[24] We define High Tech sectors using STEM employment shares following Goldschlag and Miranda (2020), who have updated the approach developed by Hecker (2005). This classification has recently been used to study the dynamics of High Tech industries in Decker et al. (2020).

[25] While these these skill-intensive industry measures are related, they are not perfectly correlated with one another. Appendix Table A5 shows the correlation between the High Tech, abstract task, and college intensive measures. The highest correlation is between college intensive and abstract task intensive at 0.5041, which suggests that these different measures capture distinct dimensions of skill intensity.

Tate and Yang (2016). Specifically, for each pair of industries, we measure the frequency with which job changers move between the two industries as a fraction of the total number of job changers in the two industries. As most job changes occur within industries, industry-relevant experience is the highest when the deceased person had previously worked in the same industry. As shown in the final two columns of Table 5, we find that while the effects are stronger when losing a founder with more industry-relevant experience, the estimated coefficients are not statistically significant. Similarly, we find no evidence that losing an early joiner with industry-relevant experience is more detrimental.

Taken together, we find that the importance of early joiners and founders can vary by skill measures. More general measures of skill, such as the share of workers with a college degree, appears to have a greater effect on the importance of early joiners. Effects do not appear to vary, however, based upon the intensity of STEM or abstract-task intensive occupations, suggesting that the college skill effects are not driven by more technical college degrees. Finally, the industry-relevant experience of individuals does not appear to mediate the effects of losing either an early joiner or founder.

5.3 Robustness Analyses

In this section, we posit and test several alternative explanations that are consistent with the main results. In doing so, we establish robustness of the organization capital hypothesis and verify the validity of our sample construction and measurement.

5.3.1 Second Year Joiners

Our results highlight that early joiners play a critical role in the performance of startups—not as important as founders but still having a substantial and persistent effect on scale. The adverse effects of losing an early joiner are larger and more persistent than the effects of losing an employee at small businesses (Jäger and Heining, 2022). To provide more perspective on the difference between early joiners and employees at small businesses, we consider the impact of losing a second-year joiner on firm performance. We follow the same matching and specification approach in our main analysis, identifying firms that experience the premature death of an employee that joined the firm in its second year of operation and a similar control firm that did not. We exclude from this analysis firms with the loss of either a founder or early joiner.

Results for second year joiners are reported in Figure 4 for TVV/DHS outcomes.[26] We find non-trivial, negative, and transitory effects of losing a second year joiner. The transitory nature of the second year joiner effects is markedly different from the persistent effects for early joiners. The effect peaks within two years and becomes insignificant by five years. Qualitatively, the effects of losing a second year joiner are similar to those of losing a worker at a small firm (Jäger and Heining, 2022). These results imply that, unlike early joiners whose contribution is long-lasting, later joiners appear to be readily replaceable.

5.3.2 Persistence of the Effect

While we find that the negative impacts of a initial team member death shock are persistent through five years after the shock, it is instructive to consider how long these effects last. Long-lasting negative effects may indicate that disruptions caused by the initial team member loss are not easily resolved by replacement hiring. It is possible that catch-up dynamics occurring outside of the five-year window in our baseline analyses result in treated firms converging with their matched counterparts over a longer time horizon. To investigate this possibility, we re-estimate the regression equation (1) and compare the differences in firms' performance through 10 years after the shock.

We show in Figure B9 in the Appendix that the negative effects for employment and revenue are remarkably persistent and do not dissipate even 10 years after the shock. Treated firms appear to partially recover between 1 and 2 years after the shock but never fully return to their pre-shock performance. These results reinforce our view that initial team members

[26] Appendix Figure B8 shows *log*-based results.

are not easily replaceable as organization capital is largely inalienable from them.

5.3.3 Small-Business-Intensive Industries

Rather than organization capital, our main results may be driven by particular industries where small business owner-operators are particularly important. Hurst and Pugsley (2011) highlight that in a subset of industries, small business activity is dominated by firms that tend to operate with small natural scale of production, and their operation depends heavily on the human capital and labor supply of business owners. Examples of these are service industries where skilled craftsmen have gone into business for themselves. One might argue that a plumbing business with one owner will necessarily exit if the owner-plumber dies unexpectedly. Moreover, initial teams in these industries are generally small and the probability of the deceased initial team member being one of the business owners is relatively high.[27] While potentially related, a tight link between owner death and firm exit when the natural scale of production is small is distinct from our organization capital hypothesis.

To test this possibility, we estimate heterogeneous treatment effects using a small-business-intensive industry indicator. Following Hurst and Pugsley (2011), we define small-business-intensive industries (HP industries) as the top 40 four-digit NAICS industries in terms of the share of small firms (those with less than 20 employees) out of all firms in the same industry. Results are shown in Table A6 in the Appendix, which indicate no statistically different effects in the HP industries compared to the non-HP industries. Moreover, the estimated effects for non-HP industries are similar in magnitude to the main effects shown in Table 3, indicating that the main results are not primarily driven by small-business-intensive industries. This finding is inconsistent with the hypothesis that our main results are driven by deaths occurring in small, family-owned businesses or those of plumbers or skilled-craftsmen,

[27] Note that the death of a business owner does not necessarily lead to business closure if there are multiple owners. Kerr and Kerr (2017) document that the average number of owners for new businesses in the U.S. is around two. In addition, even if the owner of a single-owner business dies, it does not close if another entity acquires the business and continues its operation.

whose business operations are mostly tied to the owners' human capital and labor. Even in small-business-intensive industries, early joiners play a critical role in startup performance.

5.3.4 Emotional Distress

An important alternative explanation of our findings is the emotional distress that results from the loss of a coworker, which negatively impacts the motivation and productivity of the surviving members of the startup. Rather than the loss of organization capital, it may be the interpersonal shock associated with the death of a colleague that explains the post-shock decline in firm performance. While we cannot directly observe and control for the emotional well-being of individuals, our results do not support emotional distress as the primary mechanism. For one, we find that the negative impact on firm performance increases with the prior earnings of the deceased initial team member (see Appendix Table F1). Insofar as losing a coworker is a traumatizing event in and of itself, it is unlikely that the severity of the emotional toll is proportional to the prior earnings of the deceased individual. The same logic applies to the differential impact by the loss of founders versus early joiners and the industry of the startup (for example, B2B- versus B2C-oriented). Furthermore, one might expect the emotional shock to gradually subside, especially given the substantial turnover among young firms. Our findings, however, show that the negative impacts persist even 10 years after the death shock. While we cannot rule out the importance of psychological stress induced from losing a coworker, our results do not support this factor as a primary mechanism underlying the link between the loss of a initial team member and startup performance.

5.3.5 Selection Effects from Employee Turnover

Finally, as illustrated in Figure B4 in the Appendix, both founders and early joiners exhibit considerable attrition—especially among those with lower prior earnings—in the first few years after startup. This pattern suggests that startups that survive beyond the initial few years are left with a selected set of individuals from the initial team members. As such, our treatment effect may be primarily driven by "older" startups whose remaining workers are positively selected and therefore more valuable to the firm. We empirically examine this view by testing whether the effects are systematically different between startups treated at firm age 0-1 or those treated a firm age 2-5. As shown in Appendix Table A4, we find no significant differences associated with startups between the two groups when losing an early joiner, though we find slightly weaker effects for losing a founder for startups shocked at firm age 2-5. Nonetheless, the main effects for both founders and early joiners remain negative and significant, implying that they are robust even for startups shocked at firm age 0-1. Our main findings are robust to the selection effects driven by employee turnover and the types of workers that remain after the firm's first years of operation.

6 Concluding Remarks

Using employee-employer matched data with administrative tax information on all new employer startups in the U.S., we demonstrate that early joiners are critical drivers of startup performance. Unlike other rank-and-file employees who may be readily replaceable (e.g. second year joiners), early joiners tend to leave a lasting legacy on the performance of their nascent employers. We find that the impact of early joiners differs from that of founders. Early joiners are relatively more important on the intensive margin and as the firm ages. We hypothesize that the impact of early joiners stems from their contribution to the organization capital that emerges at firm formation and becomes embodied in the early joiners. In support of this view, we find that the impact of both founders and early joiners is stronger in contexts where the role of organization capital is expected to be heightened.

We conclude by discussing three avenues for future research. First, while the focus of this study has been on the importance of initial teams in determining startup performance, an important question is whether and how the human capital quality of initial teams has evolved over time. With declining dynamism (Decker et al., 2014) and rising concentration among large employers (Autor et al., 2020), a possibility is that high-ability individuals are increasingly heading towards established companies rather than startups—potentially leading to a deterioration in the human capital quality of initial teams over the past few decades.

Second, one can ask what explains the positive assortative matching between founder quality and early joiner quality, as evidenced in our descriptive analysis. It could be that high-quality founders possess the managerial skills to recruit the best talent from the labor market. A more passive view is that these dynamics simply reflect these individuals' underlying social networks; that is, talented founders and early joiners are likely to emerge from shared social contexts (e.g., prior employer or school) that systematically attract similar individuals. While both point to an advantage for high-quality founders in assembling a talented team, the real sources of such advantage remain less clear.

Third, future research can further examine the high attrition of initial teams as documented in this study. While we primarily focus on exogenous separations (i.e., premature deaths) to aid our analysis of causal relationships, additional research can make progress on these questions by *embracing* the endogenous nature of turnover ranging from voluntary departures to dismissals. For instance, how might external labor markets shape the voluntary versus involuntary turnover patterns of early joiners either through frictions (e.g., non-compete agreements) as well as opportunities (e.g., better outside options)? Given that young firms account for a significant share of economy-wide job creation, a deeper understanding of the career dynamics of startup joiners appears to be an important line of inquiry.

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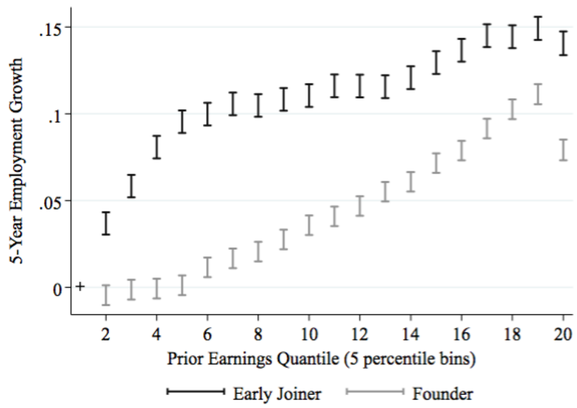
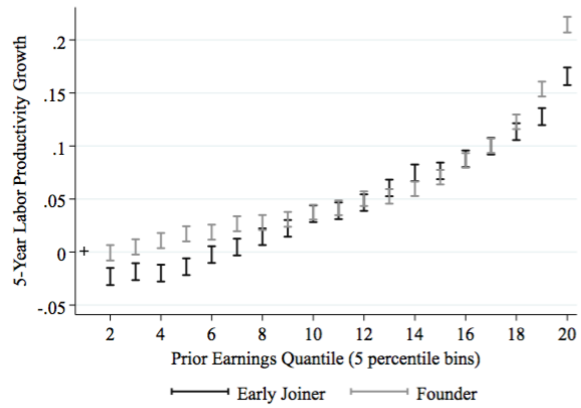
Figures

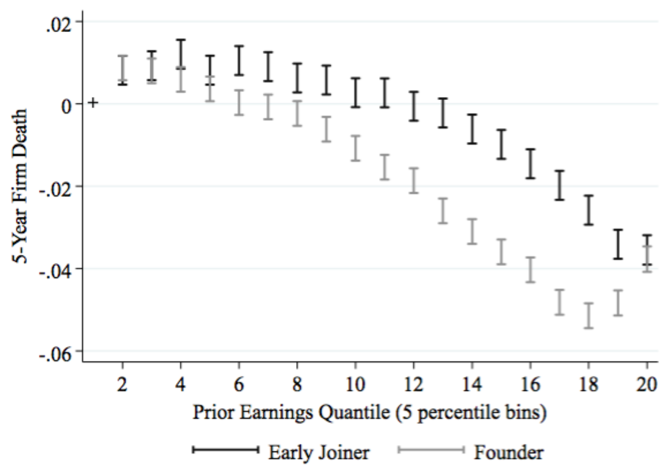
Figure 1: Founder and Early Joiner Prior Earnings and Startup Outcomes



(a) Employment Growth and Prior Earnings



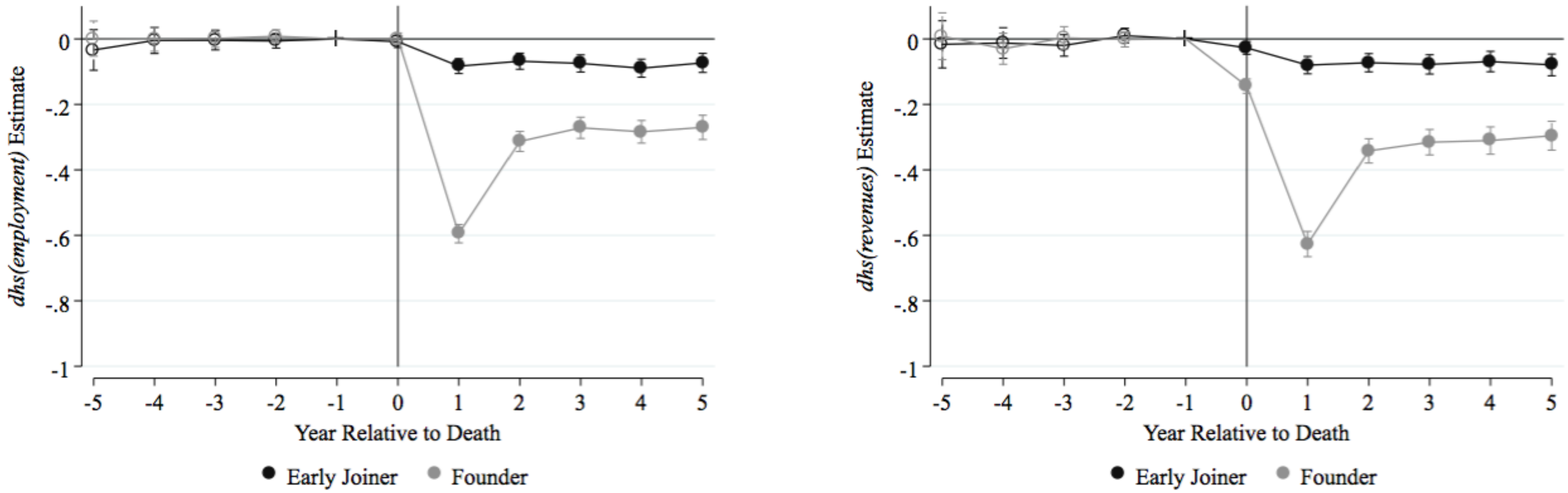
(b) Productivity Growth and Prior Earnings



(c) Firm Death and Prior Earnings

Notes: The source for all figures and tables is the Initial Team Database (LBD, LEHD), author's calculations. Controlling for industry-year effects and initial employment in employment growth and exit regressions and initial labor productivity for labor productivity growth regressions. Shown are 95% confidence interval estimates for each prior earnings bin. Estimates are relative to reference group prior earnings bin 1.

Figure 2: Impact of Founder and Early Joiner Death on $dhs(employment)$ and $dhs(revenues)$

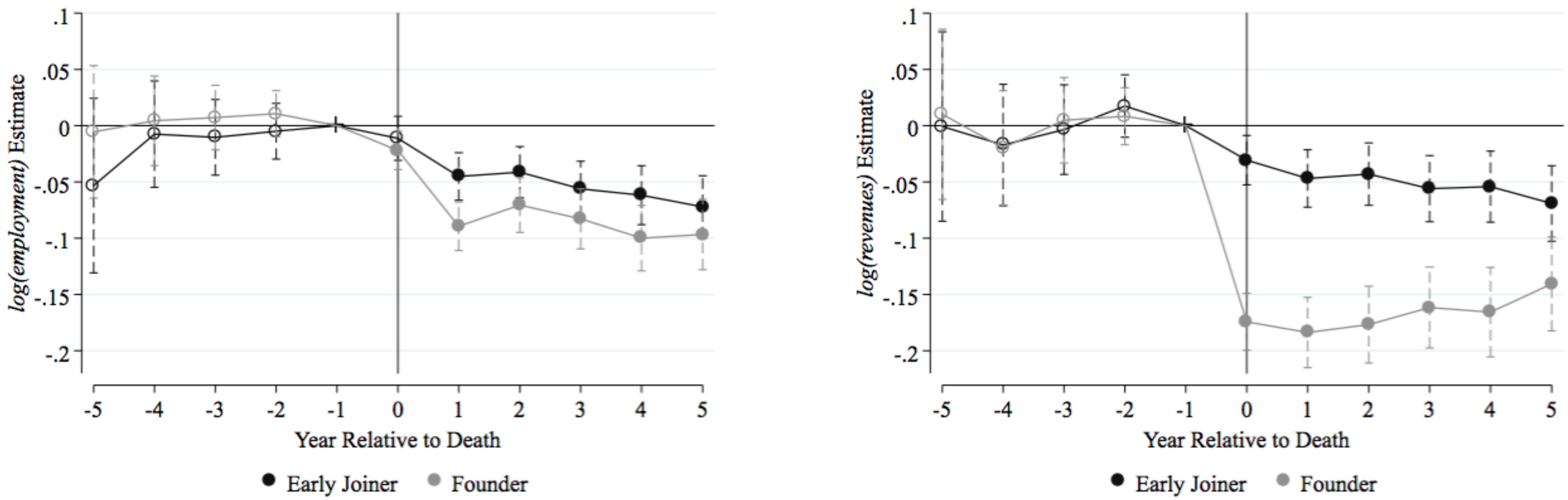


(a) Employment

(b) Revenues

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. In this figure and subsequent tables and figures we use the abbreviation dhs for the TVV/DHS transformation.

Figure 3: Impact of Founder and Early Joiner Death on $log(employment)$ and $log(revenues)$

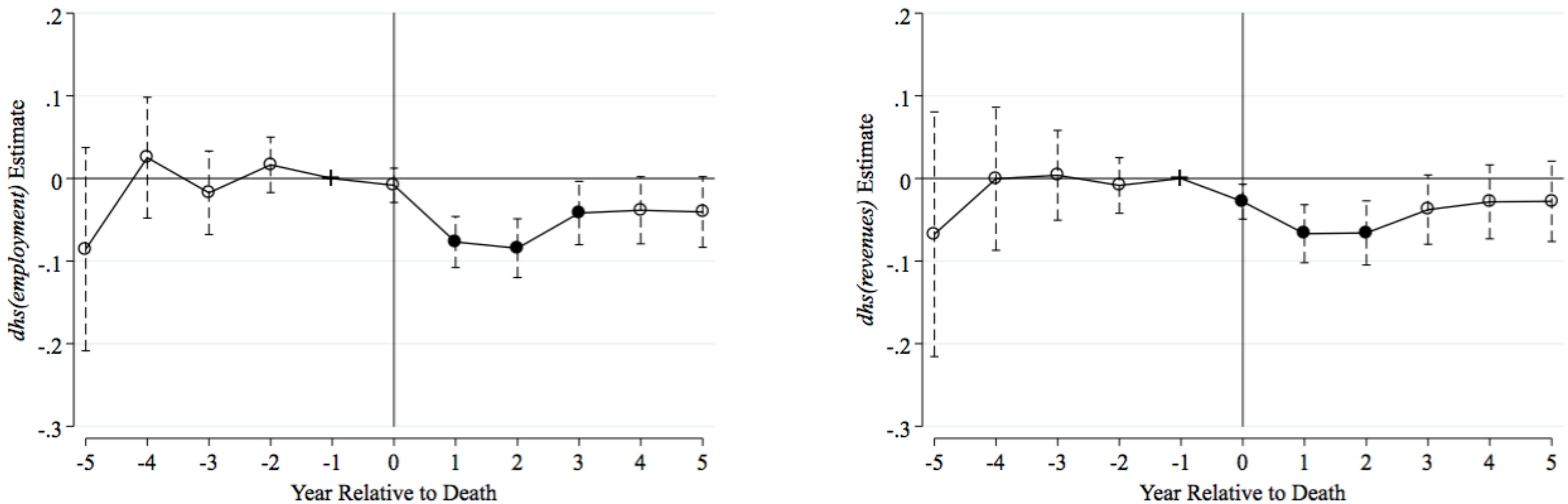


(a) Employment

(b) Revenues

Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t - 1$.

Figure 4: Impact of Second Year Joiner Death



(a) Employment

(b) Revenues

Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t-1$.

Tables

Table 1: Summary Statistics on Treated and Controls in Death Shock Year

	Treated	Control	Difference	Std. Err.
Firm Age	1.432	1.436	.003589	.01377
Employment	15.82	14.41	-1.418	.2995
log(Employment)	1.979	1.91	-.06835	.01047
log(Revenue)	6.456	6.451	-.005148	.01447
log(Labor Productivity)	4.381	4.507	.1263	.01161
Avg Age of FT	40.78	40.74	-.04872	.07288

Notes: Means of key variables for the treated (premature death shock cases) and matched control firms are based in the death shock year. Natural log is used for employment, revenue, and labor productivity. Table shows difference between treated and control along with the corresponding standard error of the difference.

Table 2: Firm Death Linear Probability Model

	Firm Death				
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: Founder Death					
Treated	.2586***	.2721***	.263***	.2536***	.2433***
	(.01409)	(.01381)	(.01296)	(.01248)	(.01194)
R^2	.2912	.272	.2583	.2566	.2565
N	21500	21500	21500	21500	21500
Panel B: Early Joiner Death					
Treated	.02317***	.03255***	.03598***	.03906***	.03717***
	(.003402)	(.00495)	(.00532)	(.005206)	(.006431)
R^2	.1058	.1229	.1389	.1541	.1661
N	31500	31500	31500	31500	31500

Notes: Controlling for industry-year, state, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column shows estimates where the LHS variable is a binary indicator equal to 1 if the firm exits some number of years after the premature death shock. Observation counts rounded to avoid the disclosure of sensitive information in this and all subsequent tables. The mean of the LHS variable among control firms, which captures the firm death rate some number of years after the premature death shock is shown at the bottom of the table.

Table 3: Founder vs. Early Joiner Effects

	$dhs(emp)$	$dhs(rev)$	$log(emp)$	$log(rev)$
Post × Treated	-.05881***	-.06125***	-.03583***	-.05057***
	(.009723)	(.01189)	(.009717)	(.01207)
Post × Treated × Founder	-.2303***	-.275***	-.03397**	-.126***
	(.01449)	(.01913)	(.01362)	(.01829)
R^2	.3908	.4146	.8767	.8918
N	316000	204000	290000	210000

Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Regression specifications also include *Post* and $Post \times Founder$, the estimates for which are excluded for simplicity.

Table 4: Founders & Early Joiners Heterogeneous Effects

	Young Firm		B2B		Small Team		Sole Proprietorship	
	$dhs(emp)$	$dhs(rev)$	$dhs(emp)$	$dhs(rev)$	$dhs(emp)$	$dhs(rev)$	$dhs(emp)$	$dhs(rev)$
P × T	-.1092***	-.1103***	-.039**	-.03924**	-.0264**	-.03961**	-.07346***	-.068***
	(.01488)	(.01784)	(.01219)	(.0147)	(.01236)	(.01455)	(.01047)	(.01237)
P × T × F	-.1598***	-.2099***	-.2234***	-.2322***	-.08856**	-.05289	-.1541***	-.2211***
	(.02065)	(.02641)	(.01877)	(.02437)	(.0275)	(.03317)	(.01628)	(.02022)
P × T × [Het Eff]	.05095**	.05059**	-.04315**	-.04753**	-.07448***	-.05235**	.088**	.07537*
	(.01776)	(.02143)	(.01977)	(.02423)	(.01976)	(.02449)	(.02871)	(.04409)
P × T × [Het Eff] × F	-.06948**	-.06595**	-.01321	-.08326**	-.1317***	-.2431***	-.2694***	-.3395***
	(.02519)	(.03257)	(.02929)	(.03856)	(.03369)	(.04211)	(.03771)	(.06163)
R^2	.377	.4005	.3908	.4149	.3915	.4158	.3923	.4161
N	412000	275000	316000	204000	316000	204000	314000	204000

Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P, T, F are *Post*, *Treated*, and *Founder* respectively. Regressions also include P and $P \times [HetEff]$ which are not reported for simplicity. $YoungFirm$, *B2B*, *SmallTeam*, and *Sole Proprietorship* indicate the firm is five years old or younger in the treated year, the firm is in a *B2B*-intensive industry, the firm has five or fewer active founding team members in the treated year, and the firm is a sole proprietorship, respectively.

Table 5: Founders, Early Joiners, and Skill

	College Share		High Tech		Abstract Task		Industry-Relevant Exp.	
	$dhs(emp)$	$dhs(rev)$	$dhs(emp)$	$dhs(rev)$	$dhs(emp)$	$dhs(rev)$	$dhs(emp)$	$dhs(rev)$
P × T	-.06144***	-.06414***	-.05723***	-.06027***	-.061***	-.06351***	-.05016***	-.04434***
	(.00981)	(.01205)	(.009835)	(.01195)	(.009788)	(.01202)	(.01105)	(.01319)
P × T × F	-.2267***	-.2685***	-.2324***	-.273***	-.2282***	-.2726***	-.2141***	-.2539***
	(.01459)	(.01918)	(.01468)	(.01932)	(.01468)	(.01932)	(.01661)	(.02141)
P × T × [Het Eff]	-.1846**	-.1667*	-.04486	-.02813	-.05175	-.04584	.01901	-.01183
	(.07203)	(.09416)	(.06074)	(.0833)	(.04344)	(.05313)	(.061)	(.07391)
P × T × [Het Eff] × F	-.03135	-.1356	.06098	-.04751	.01155	.034	.05762	-.03636
	(.09958)	(.1372)	(.08749)	(.1211)	(.06069)	(.07956)	(.09601)	(.1225)
R^2	.391	.4149	.3908	.4147	.391	.4147	.3959	.4218
N	314000	204000	316000	204000	314000	204000	241000	163000

Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P, T, F are *Post*, *Treated*, and *Founder* respectively. Regressions specifications also include P and $P \times [HetEff]$ which are not reported for simplicity. *College Share* is the share of workers with a bachelor's degree or higher in the industry of the startups, averaged over 1990-2015. *High Tech* indicates the firm is in a High Tech industry, and *Abstract Task* is the employment share in abstract task-intensive occupation in each industry. *Industry − Relevant Exp.* between the industries of the focal startup and the deceased individual's prior employer is the frequency with which job changers move between the two industries as a fraction of the total number of job changers in the two industries.

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.

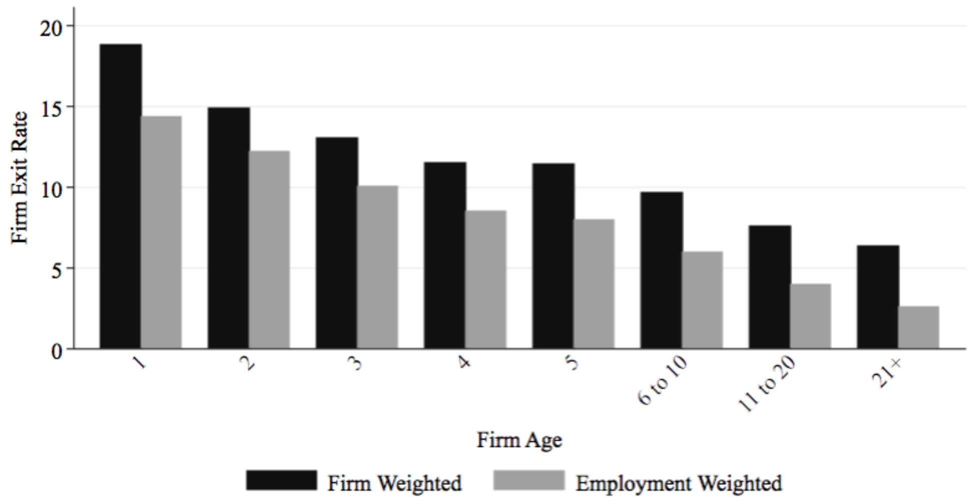
Table A6: Small Business Intensive Sectors

	$dhs(emp)$	$dhs(rev)$
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.

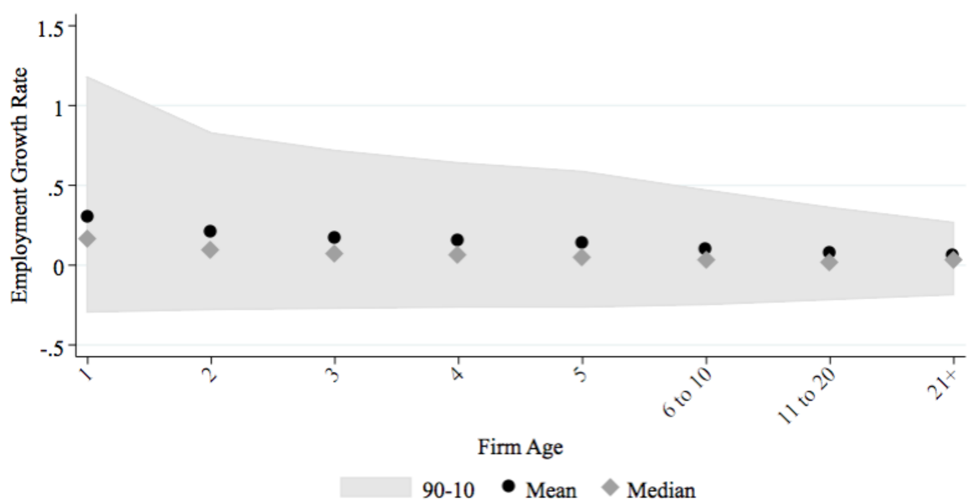
B Additional Figures

Figure B1: Firm Exit Rates and Firm Age



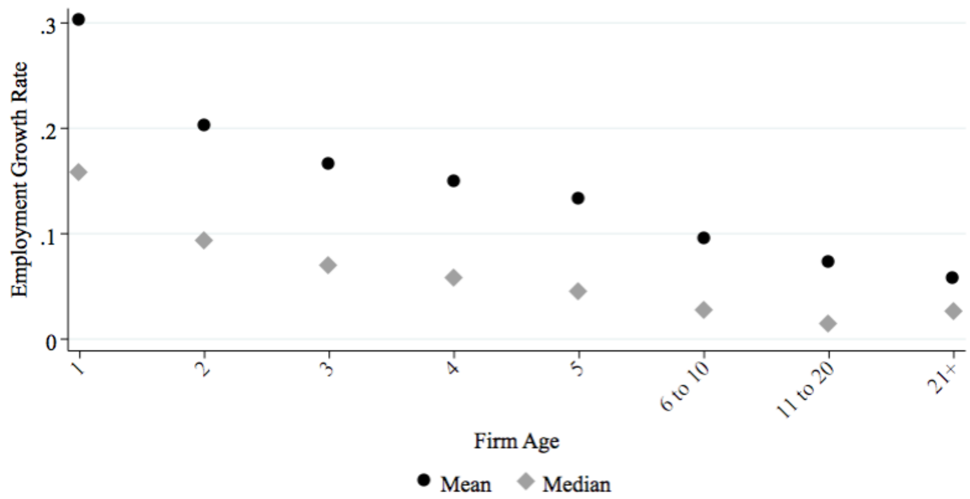
Source: Initial Team Database (LBD, LEHD), author's calculations.

Figure B2: Firm Age and Employment Growth



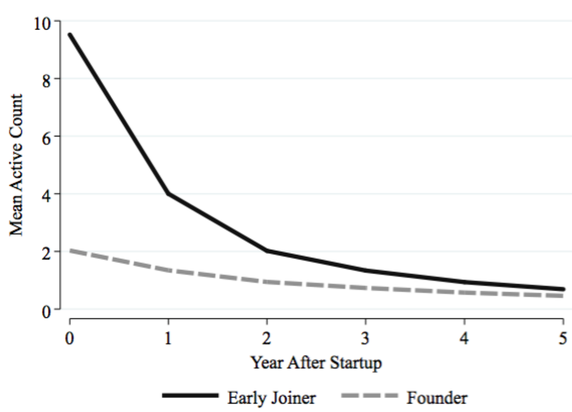
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Employment-weighted distribution.

Figure B3: Firm Age and Mean and Median Employment Growth

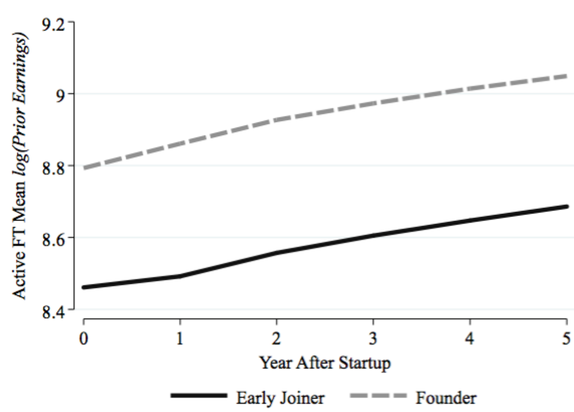


Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Employment-weighted distribution.

Figure B4: Founder and Early Joiner Attrition and Prior Earnings



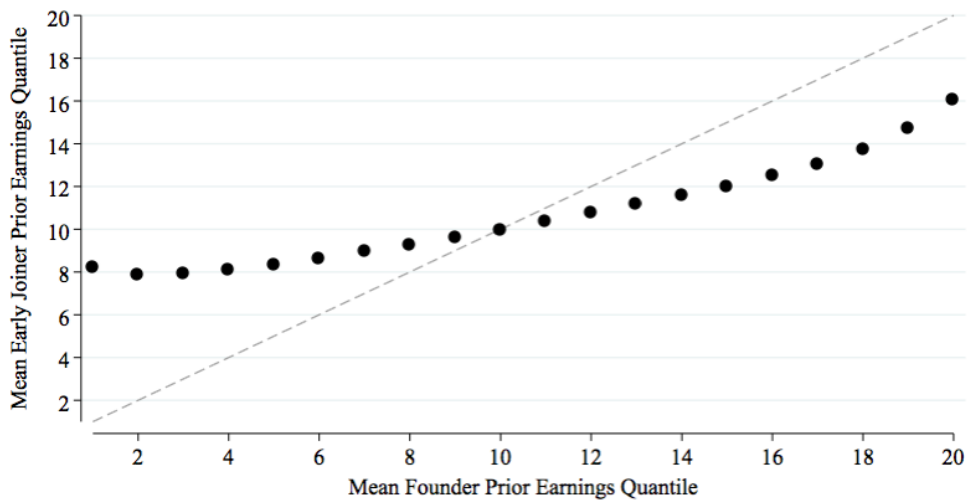
(a) Attrition of Founders, Early Joiners



(b) Prior Earnings of Active Founders, Early Joiners

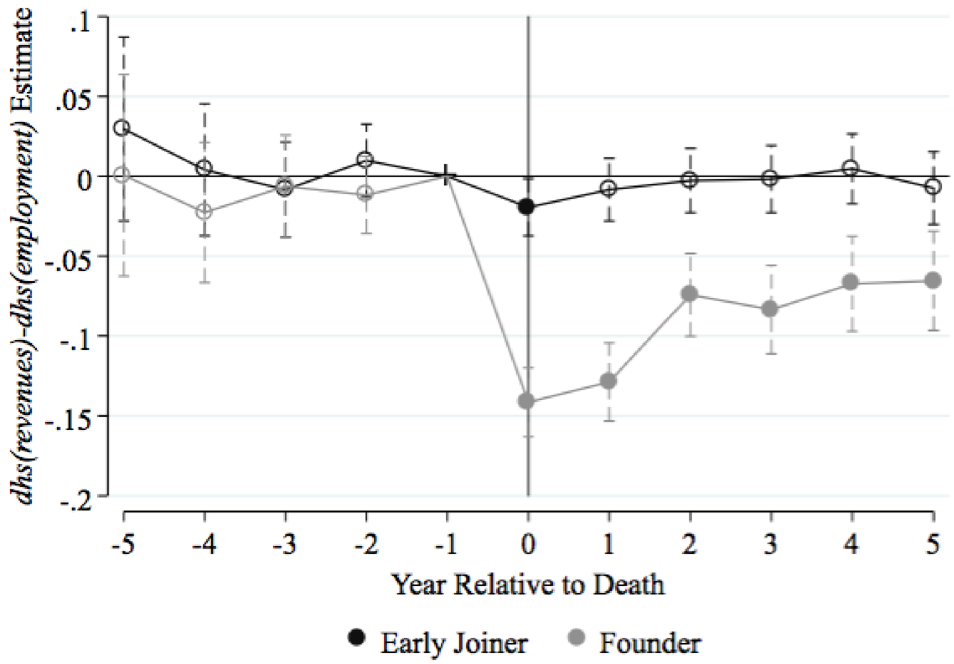
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Mean count of active (earnings positive) founders and early joiners each year after startup (a) and mean active founder and early joiner log prior earnings (b).

Figure B5: Prior Earnings Composition of Founders and Early Joiners



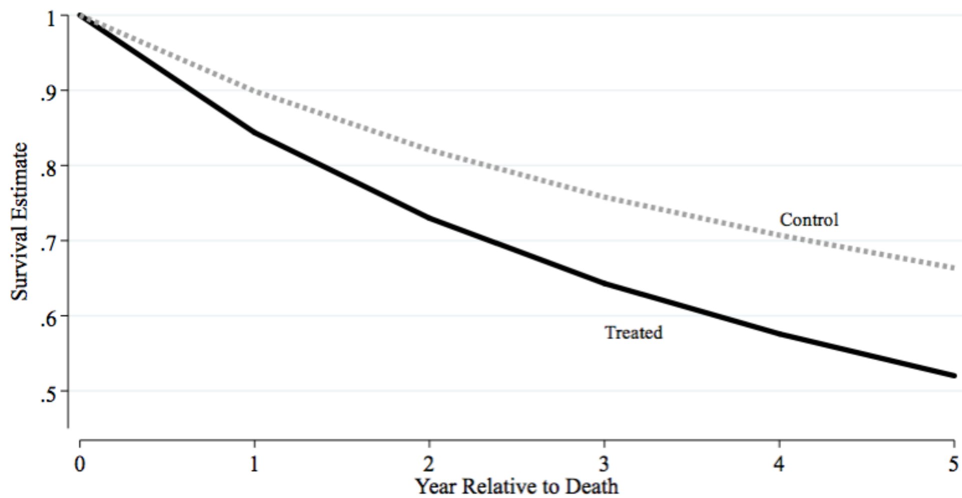
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Mean early joiner prior earnings quantile bin for each founder prior earnings quantile bin. 45° shown to emphasis when founder prior earnings position is equal to early joiner prior earnings position.

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



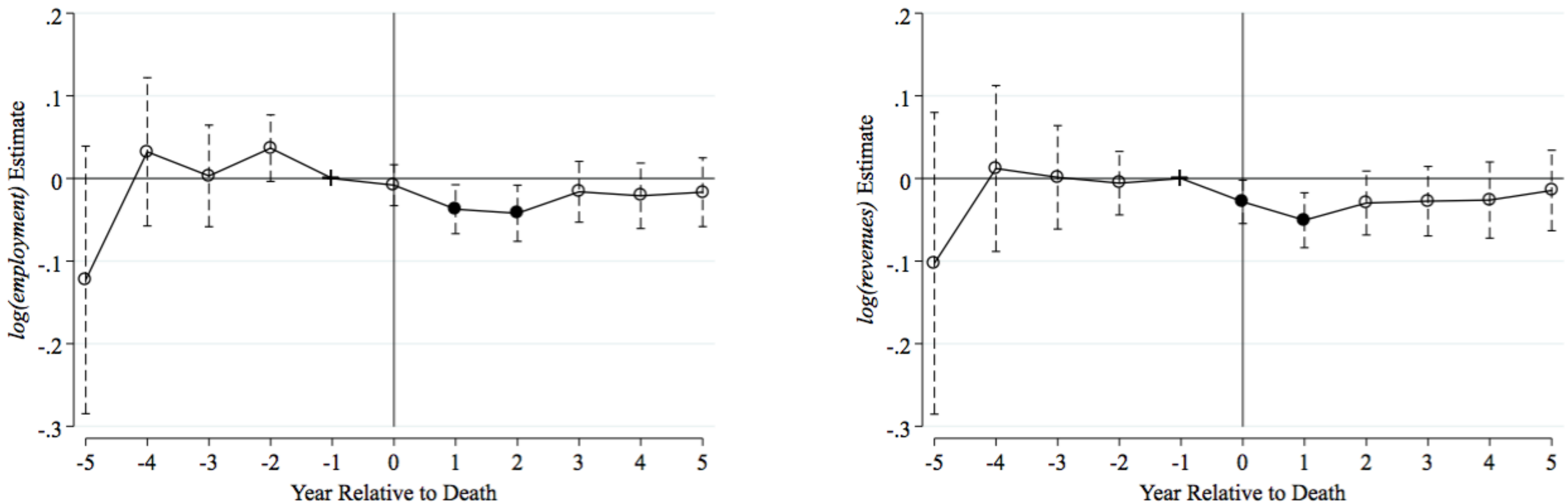
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t-1$. Points shifted around time periods, early joiner left and founder right, to ease interpretation.

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.

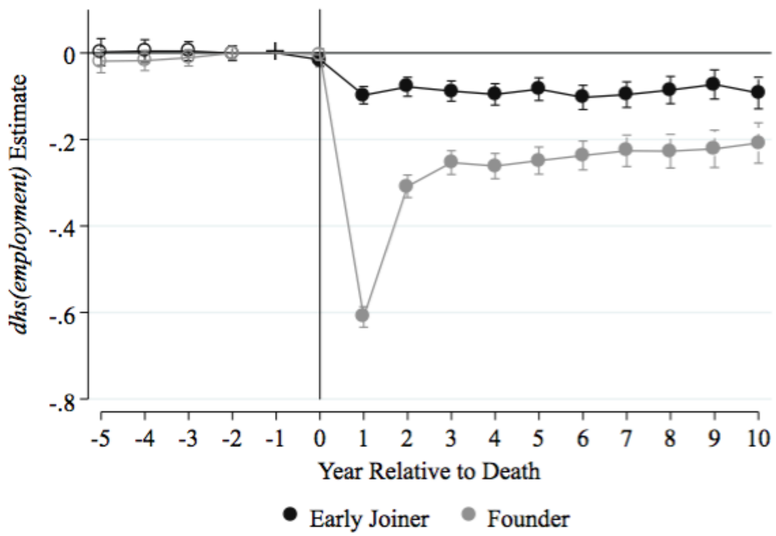
Figure B8: Impact of Second Year Joiners Death on *log* Outcomes



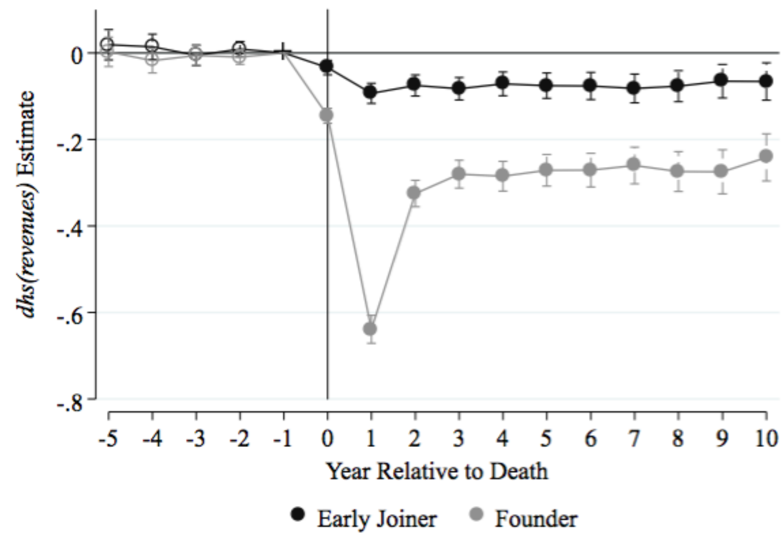
(a) Employment (b) Revenues

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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