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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 explaining firm performance. We use administrative employer- employee matched data on all US startups and utilize the premature death of workers as a natural experiment exogenously separating talent from young firms. We find that losing an early joiner has a large negative effect on firm size that persists for at least ten years. When compared to that of a founder, losing an early joiner has a smaller effect on firm death but intensive margin effects on firm size are similar in magnitude. In contrast, losing a later joiner yields only a small and temporary decline in firm performance. We provide evidence that is consistent with the idea that organizational 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, Haltiwanger, Jarmin, and Miranda, 2014; Pugsley, Sedlek, and Sterk, 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). Much evidence has acummulated in support of the critical role of founders in setting the initial vision and shaping the growth and performance of their ventures (Kaplan, Sensoy, and Strömberg, 2009; Agarwal, Braguinsky, and Ohyama, 2020; Smith, Yagan, Zidar, and Zwick, 2019; Becker and Hvide, 2021).[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 organizational capital that distinguishes a new firm.

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. A few years after joining she 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, Meyer's legacy at Google continues to persist as her pioneering work on Google's first homepage and advertising-based

[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, Eifert, Mahajan, McKenzie, and Roberts (2013).

revenue model helped lay the foundations of the company's core business model.

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 organizational capital that becomes embodied in, and thus inalienable from, the team members themselves. They are therefore not easily replaceable with outside individuals and losing an initial team member can result in the loss of accumulated organizational 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 business owners of sole proprietors whose identities are obtained from income tax filings. Our focus is on startups that organize themselves as sole proprietors or corporations, as we can measure initial teams of those firms in a consistent manner; we exclude partnerships because their business owners are prohibited from paying themselves 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, Jones, Kim, and Miranda, 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 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 human capital, 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 human capital 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 employment and revenue by 8 and 12 percent, respectively, and the negative effects do not dissipate even 10 years after the shock, implying that disruptions caused by loss of an early joiner is 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, Yagan, Zidar, and Zwick, 2019; Becker and Hvide, 2021). We use founder effects as a benchmark for interpreting the magnitude of early joiner effects. Losing either a founder or early joiner lowers the likelihood of firm survival. However, the extensive margin impact 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 adverse impact of losing an early joiner on the intensive margin is almost as large as for losing a founder.

To provide perspective on why early joiners matter, we explore a number of heterogeneous treatment effects in settings in which the importance of organizational capital from early joiners is expected to be amplified or attenuated. Delgado and Mills (2020) provide persuasive evidence that organizational 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, by phase in the firms' life cycle (the first five or second five years after startup) and by whether the firm is in the high-tech industry as measured by STEM-intensity of the workforce.

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 Jager and Heining (2019) 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 examine the loss of an initial team member based on the relative ex ante human capital. As might be expected, we find that the loss of an initial team member with higher relative human capital has a larger adverse impact on the startup. Importantly, however, the loss of an initial team member at the average of the within-firm human capital 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 organizational 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

Our work builds on two recent studies that use a similar identification strategy to quantity the contribution of founders to firm performance. Smith, Yagan, Zidar, and Zwick (2019) find large and persistent negative effects on pass-through profit from premature deaths of business owners. They use rich 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 (2021) investigates the impact of losing founders from pre-mature deaths on startups using administrative data for Norway. They find large, adverse, and persistent impacts of losing founders on a number of outcomes including survival, employment, revenue, and profits. Our findings on founders are broadly consistent with both of these studies. We build on this work by broadening the focus to the entire initial team and highlighting the contribution of early joiners to 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 Jager and Heining (2019).

We are not the first to hypothesize that early joiners may play a role in shaping the trajectory of startups. A handful of studies examine issues such as the characteristics of early joiners, their preferences for joining startups, and the impact of early joiners in generating persistence in how tasks are performed (Roach and Sauermann, 2015; Burton and Beckman, 2007; Kim, 2018). Our findings complement these studies by providing causal evidence that losing an early joiner can lead to a large persistent drop in startup performance.

Our work also contributes to the entrepreneurship literature by exploring initial team human capital as an important determinant of startup growth. 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, Jones, Kim, and Miranda, 2020), and the name or the incorporation location of the business (Guzman and Stern, 2017). Our findings highlight the importance of taking into account the human capital contributions of early joiners.

Our work also builds upon the firm dynamics literature. Several empirical studies have stressed that high-growth young firms play a disproportionate role in aggregate job creation and productivity growth (Decker, Haltiwanger, Jarmin, and Miranda, 2016; Alon, Berger, Dent, and Pugsley, 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 an important role, and we contribute to this literature by identifying initial teams as a salient initial firm characteristic (Pugsley, Sedlek, and Sterk, 2021). 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 organizational capital that makes firms distinct. An illustrative model that formalizes this organizational capital interpretation of the startup process is presented in Appendix A.1. 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 organizational 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 organizational capital? A narrow view is that it is only the founders that contribute while a broader view is that the all initial team members make important contributions. A second issue is the extent to which organizational capital is embodied in the initial team. If the organizational capital is inalienable, then the loss of an initial team member will have an adverse impact on firm performance. As shown in the appendix, 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). Information on startups is derived from the LBD. 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, Jarmin, Kulick, and Miranda (2017). 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

[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. For example, identifiers may change over time due to 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.

survival.[3] As our focus is on investigating the heterogeneity in outcomes within narrowly defined sectors, we control for detailed industry by year effects in our analysis.

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.[4] 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.[5] 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

[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 labor productivity. While the evidence shows that revenue labor productivity is positively correlated with technical efficiency and demand shocks (see, e.g., Decker, Haltiwanger, Jarmin, and Miranda (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.

[4]For example, the IRS 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." See https://www.irs.gov/businesses/small-businesses-self-employed/s-corporation-employees-shareholders-and-corporate-officers.

[5]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.

virtually all C corporation startups are privately held.[6] 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.

While the existing entrepreneurship literature focuses almost exclusively on founders, partly because of data limitations, we decompose the initial team into two groups: founders and early joiners.[7] 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, Jones, Kim, and Miranda (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. 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, Jones, Kim, and Miranda (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

[6] Also, see https://www.irs.gov/businesses/small-businesses-self-employed/paying-yourself, 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.

[7] For a few exceptions studying non-founding employees of startups, see Ouimet and Zarutskie (2014), Dahl and Klepper (2015), Roach and Sauermann (2015), and Kim (2018).

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% respectively.[8]

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.

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.[9] An important feature of this approach is that prior earnings are an ex-ante characterization of each individual. Therefore, they are a useful proxy for human capital and also serve as a robustness check to our founder definition. In the following section, we establish some basic facts in the relationship between human capital of the initial team — separately for founders and early joiners — and firm outcomes.

Our analytical database 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

[8] Note that, unlike Nelson (2016) and Hyatt, Murray, and Sandusky (2021), Azoulay, Jones, Kim, and Miranda (2020) is based on employer startups in the LBD.

[9] 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, 2021). For some jobs, individuals will not have a prior earnings. Therefore, analyses using prior earnings will be limited to jobs where prior earnings is not missing.

the LEHD infrastructure. State-level coverage in the LEHD varies over time but by 2000 coverage is nationally representative.

4 Basic Facts about Firm Outcomes and Initial Teams

Before exploring the relationship between human capital 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. In addition, we find that this heterogeneity in outcomes is tightly linked to productivity: firms with higher realized productivity are more likely to survive and grow. These results can be found in Figures A1, A2, and A3 and Table A1 in the appendix.

Turning to the characteristics of initial teams, we find systematic and statistically significant relationships between the human capital 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 human capital. Then we regress five-year employment and productivity growth rate outcomes and a binary indicator reflecting firm exit on the human capital 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-human-capital 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 human capital distribution except for the very top for employment growth and exit outcomes.

Leveraging the longitudinal structure of our data, we examine post-entry attrition patterns among founders and early joiners. Figure 2 shows the average number of founders and early joiners remaining at the firms in the years since startup (panel (a)) and their human capital (panel (b)). We find that attrition is significant for both founders and early joiners, while it is notably higher for the latter. Interestingly, attrition among the initial team generally stems from the bottom of the human capital distribution. That is, conditional on survival, the average human capital 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. As shown in Figure 3, founders with high human capital tend to associate with early joiners with high human capital.

In short, we find that the human capital 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. To identify causal relationships, we leverage exogenous variation in the initial team due to premature death, which we turn to next.

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-difference 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.[10] Following Jaravel, Petkova, and Bell (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.[11] 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.[12] 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, Iacus, King, and Porro, 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

[10]The date of death information is obtained through several sources including first-party reports from family members or representatives and verified third-party reports from friends, state governments, Centers for Medicare and Medicate Services, Department of Veterans Affairs, and the Internal Revenue Service. Finlay and Genadek (2021) show, in part due to recent data quality improvements to the SSA death reports, death counts from the Census Numident are similar to counts produced by the Centers for Disease Control and Prevention even at the weekly frequency.

[11]For examples of studies using premature deaths for identification purposes see Jones and Olken (2005); Nguyen and Nielsen (2010); Azoulay, Graff Zivin, and Wang (2010) and Oettl (2012).

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

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 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.[13] The sample is reduced for revenue-based measures, as only about 80% of firms in the LBD are assigned revenue values.[14] 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 scale measures such as employment and revenue, and survival of firms. For employment and revenue, we apply the inverse hyperbolic sine (*ihs*) transformation, which enables us to estimate the impact of treatment inclusive of the intensive and extensive margins.[15] 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).

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

[14] Haltiwanger, Jarmin, Kulick, and Miranda (2017) show that the pattern of missingness for revenue is approximately random.

[15] The inverse hyperbolic sine approximates the log transformation but permits inclusion of zeroes. $ihs(x) = ln(x + (1 + x^2)^{0.5})$. Burbidge, Magee, and Robb (1988) and Pence (2006) describe the advantages of the *ihs* transformation for analysis of distribution of outcomes with extensive zero values (for example, earnings, wealth, employment). Variation in *ihs* measures are approximately equivalent to log variation for x not close to zero (for x not close to zero, $ihs(x)$ is approximately equal to $ln(2x)$).

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

$Y_{i,j,t}$ 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, $\gamma_{i,t}$, and $\tau_{j,t}$ are firm, firm age, and industry by year fixed effects.[16] Estimates of δ_k are the parameters of interest, representing the change in outcomes in each year for treated firms relative to the control group.

Figure 4 displays the effect of losing a founder and that of losing an early joiner on employment (pane(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 10 percent and 14 percent, respectively.[17] 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 fundamentals. We also find that the adverse impact is larger for revenue than for employment, particularly following the death of a founder.[18] 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 the death of a founder than for an early joiner, especially in the first year after the shock, we find

[16] Firm fixed effects will capture time invariant firm characteristics. If, for example, owners with a certain important characteristic are more likely to select a specific legal form of organization, this will be absorbed by the firm fixed effects.

[17] We convert IHS estimates to percent elasticities using $exp(\delta_k) - 1$. We follow a similar procedure for log based outcomes discussed below.

[18] We estimate Equation (1) using $ihs(emp) - ihs(rev)$ as the outcome variable to confirm that the larger effect on revenue is statistically significant for founders. The results are presented in Figure A4 in the appendix.

that much of that 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 percent 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 percent (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 percent 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.[19]

We also estimate the specifications using $log(Emp)$ and $log(Rev)$ as dependent variables. These measures, by construction, condition on survival.[20] Results are presented in Figure 5. The patterns for the log-based outcomes are similar qualitatively to those for the ihs-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 ihs-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 ihs-based outcomes in Figures 4 as they only contain intensive margin effects, but they are still quantitatively large and persistent. $log(Emp)$ declines by about 7 percent and 9 percent five years following the death shock of an early joiner and a founder, respectively.

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 a such

[19]In the Appendix, we show in Figure A5 that the estimated extensive margin effects also larger when we use a Cox proportional hazard model. In the Cox estimates founder and early joiner deaths are pooled.

[20]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.

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 5 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 A2, show that growth patterns of treated and control firms that survived after treatment are indistinguishable.[21] 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 as the loss of a founder in terms of 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, Jones, Kim, and Miranda (2020), a back-of-the-envelope calculation suggests the probability that the founders include an owner is 76 percent while the probability that early joiners include an owner is 8 percent.[22] This nine-fold difference is much larger than the difference in the impact for either the *ihs* or the *log* results – and especially for the *log* results.[23]

[21] For simplicity, we combine founder and an early joiner premature death shocks in this pre-treatment growth analysis.

[22] Nelson (2016) finds that 84% of S corporations with paid employees have at least one employee owner, and Azoulay, Jones, Kim, and Miranda (2020) find that conditional on the presence of an owner among employees, 90% are among the top three earners.

[23] This nine-fold difference understates the difference in probabilities taking into account sole proprietors. According to the Statistics for US Businesses (https://www.census.gov/programs-surveys/susb/news-and-updates/updates/2021-03.html), sole proprietors account for about 20% of the employer firms that have

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).

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

$Y_{i,j,t}$ 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 ($FOUNDER_i = 1$).[24] 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 *ihs* 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 twice as large for $ihs(emp)$ and more than four times as large for $ihs(rev)$. 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 employment and revenue to decline by 8 percent and 12 percent, respectively, over the subsequent five years. The last two columns of Table 3 show the *log*-based outcomes, which as before condition on survival, capturing intensive margin effects. Consistent with Figure 5, we find that the negative impact for

less than 500 employees (few young firms have more than 500 employees) and either sole proprietors or corporations.

[24] 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.

losing a founder is larger and statistically significant, the gap is smaller than for *ihs*-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 not only founders but also early joiners play an important role in startup growth and survival, and that their impact operates both at the extensive and intensive margins.

5.2 The Relative Importance of Initial Team Members

Next, we explore whether the importance of an early joiner and a founder varies systematically depending on firm and initial team characteristics. The conceptual framework for these exercises centers around the role organizational capital plays in explaining the decline in startup performance following the loss of an initial team member. We revisit our theory of organizational capital, which we define as the tacit knowledge and resources developed in the nascent stages of a venture. If at least some organizational capital is embodied in individuals, that organizational capital is lost when an initial team member separates from the firm. The impact of losing such embodied organizational capital will depend on the context-specific salience of organizational capital. For instance, a sudden loss of organizational 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 organizational 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 B2B- versus B2C-intensive Sectors

First, 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 relationships with specific downstream customers. Goods and services for such firms have a greater degree of specificity. Consequently, a greater share of the organizational 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.[25]

Consistent with our theory of organizational capital, Table 4 shows 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 4.7 percent for employment and 9.1 percent for revenue. Relative to the baseline effect among B2C-intensive sectors, these estimates are 79% and 115% larger on employment and revenue, respectively. To compare 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 24% and 52% 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.

[25]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.

5.2.2 Small versus Large Initial Teams

Second, we 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 organizational 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.

Table 5 presents the results based on team size. Consistent with our organizational capital hypothesis, we find that losing a founder or an early joiner leads to a larger negative impact for small teams in both outcomes. The additional treatment effect associated with losing an early joiner in small teams for *ihs* employment is roughly twice as large as the baseline effect among larger teams. The impact for *ihs* revenue exhibits an even larger difference. These estimates again support the view that the main effects are driven by the loss of organizational capital associated with the lost initial team member, which will be greater among smaller teams.

5.2.3 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, Nanda, and Rhodes-Kropf, 2014) and build a customer base from the ground up (Foster, Haltiwanger, and Syverson, 2016), often in the face of financial constraints (Schmalz, Sraer, and Thesmar, 2017). Because young firms grow in multiple dimensions as they get older, the importance of founders and early joiners may change over their life cycle. Also, as young firms are underdeveloped along many dimensions, they may be especially sensitive to unanticipated shocks relative to more mature firms.[26] To investigate these possibilities, we extend our data to cover initial team member deaths that occur when

[26] Consistent with this argument, Fort, Haltiwanger, Jarmin, and Miranda (2013) show that young firms are disproportionately negatively affected by economic crises, even more so than old and small firms.

the firms are older (up to age 11). Then we compare heterogeneous treatment effects of the shock by maturity of the firms: between age 0 and 5 versus between age 6 and 11.

The results, presented in Table 6, show that the negative impact of losing an early joiner is smaller for young firms. Employment and revenue for young treated firms contracts less than for mature firms by 6 percent and 8 percent respectively. In contrast, we find that the negative impact of losing a founder is larger for young firms. The estimated coefficients indicate that the negative effects on employment and revenue are larger by 6 percent and 11 percent, respectively, for young firms. Interestingly, unlike founders, the importance of early joiners appears to grow as firms mature. Moreover, these estimates indicate that our main findings are not driven by the vulnerability of young firms.

The larger negative effect of losing a founder for young firms is consistent with our finding that losing a founder leads to a rapid decline in the probability of survival. In contrast, early joiners have less of an impact on survival but a persistent impact on the intensive margin. Apparently, the adverse effects of losing an early joiner are even larger for mature firms. We interpret this pattern as being consistent with the firm-specific human capital embodied in early joiners accumulating over time as they remain at the firm, reminiscent of the Marissa Mayer example in the introduction.

5.2.4 STEM intensive, High-Tech Businesses

Next, we examine whether the negative impact of losing a founder or an early joiner is particularly pronounced in STEM intensive industries. An industry's share of employment in STEM occupations is one method to classify industries as High Tech (Goldschlag and Miranda, 2020). Our example of Marissa Mayer at Google 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. To investigate this possibility, we compare the impact of the death shock between High Tech and non-High Tech industries. To identify High Tech industries, we use the updated STEM classification in Goldschlag and Miranda (2020), which uses STEM employment shares following Hecker (2005).[27]

As shown in Table 7, we find no evidence that effects differ between High Tech and non-High Tech industries for both founders and early joiners. In interpreting these results, it is important to emphasize that the effects in both High Tech and non-High Tech industries are significant.

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 organizational 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 (Jager and Heining (2019)). 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 6 for *ihs* outcomes.[28] We find a non-trivial, transitory negative effect of losing a second joiner for both employment and

[27] This classification has recently been used to study the dynamics of High Tech industries in Decker, Haltiwanger, Jarmin, and Miranda (2020).

[28] *log*-based effects are shown in Appendix Figure A6.

revenue. The transitory nature of the second year joiner effects is markedly different from the persistent effects for early joiners. The adverse 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 (Jager and Heining, 2019). The second year joiner results support the inference that early joiners make a unique contribution to the performance of startups.

5.3.2 Founder Definition and Human Capital

As an alternative to a dichotomous distinction between founders and early joiners, we leverage the granular human capital profile of each member. An individual's level of human capital is likely positively related to holding key leadership positions in the firm. As described in Section 3, we proxy human capital using the individual's most recent earnings before joining the startup. We examine whether losing a high-human capital initial team member is especially detrimental to startup performance. To focus on within-firm variation in human capital, we measure the extent to which a initial team's average human capital changes following the loss of a member, as shown in Equation (3).

$$HC_i = \frac{1}{N_i}(hc_i - HC_i^{FT}), \tag{3}$$

where N_i is the number of active initial team members at the firm in the quarter before the death shock, HC_i^{FT} is the average human capital of those members, and hc_i is the human capital of the deceased member. Because hc_i and HC_i^{FT} are measured in logs, HC_i measures the percentage change in the average human capital of the remaining initial team caused by the death shock.[29] If $hc_i < HC_i^{FT}$, loss of the member will increase the average human

[29] 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 human capital of the remaining initial team members.

capital of the remaining initial team, and if $hc_i > HC_i^{FT}$ the opposite will occur.

Table 9 presents interaction effects with the relative human capital variable. For relative human capital, the loss of a initial team member with average human capital among the initial team ($Post \times Treated$) yields large and statistically significant reductions in employment and revenue. For example, the impact of losing an initial team member with average human capital, inclusive of exit (*ihs*), is 14 percent for employment and 27 percent for revenue. These effects fall between the early joiner and founder estimates in Table 3. These results again support our broader focus on initial teams. It is true, however, that the loss of a initial team member with higher relative human capital yields a larger adverse effect of outcomes. For example, the loss of a initial team member with 25 log point higher human capital yields a reduction in *ihs* revenue that is about 0.18 larger (total effect of -0.48). The gap between *ihs* and *log* results is greater for the interaction effect, suggesting that losing an especially high human capital member is relatively more important on the extensive margin.

Comparing the impact of the loss of an early joiner and a mean relative human capital initial team member yields further insights. The quantitative impact of the latter is about twice that of the former. This finding suggests that not all early joiners have the same impact. At the low end of human capital, the impact is substantially smaller.[30] Putting the pieces together, our results suggest not only that founders are important, but also that the impact of a initial team member closely follows the individual's level of human capital.

5.3.3 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

[30] The results in Table 9 also imply that losing a initial team member with sufficiently low relative human capital would actually boost firm scale. Given the magnitudes of the coefficients, this outcome would typically require a initial team member with very low relative human capital; for example, for $ihs(Rev)$ it would require the deceased member to have relative human capital that is more than 40 log points below the mean.

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 find, as shown in Figure 7, that the negative effects for employment and revenue are remarkably persistent and do not dissipate even 10 years after the shock. As in our main results, 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 are not easily replaceable because organizational capital is largely inalienable from the initial team members.

5.3.4 Small-Business-Intensive Industries

Rather than organizational 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 a 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 have to exit if the owner-plumber dies unexpectedly. As the initial teams in these industries are generally small, the probability of the deceased initial team member being one of the business owners is relatively high.[31]

While potentially related, a tight link between owner death and firm exit under a small natural scale of production is distinct from our organizational capital hypothesis. One may wonder whether our results are disproportionately driven by the nature of production tech-

[31] 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.

nology of young firms in these industries rather than the organizational capital embodied in the deceased initial team member, particularly if the negative effects of the death shock is especially large when a founder dies in a small business-intensive sector.

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 10. We do not find any 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, 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.

5.3.5 Anticipation Effect

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.[32] Table 8 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.

5.3.6 Emotional Distress

Finally, 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 organizational 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 human capital of the deceased initial team member (see Table 9). 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.

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

6 Concluding Remarks

Using employee-employer data with administrative tax information on all new employer startups in the U.S., we show that the human capital of the initial team is a critical driver of startup performance. Our main contribution to the entrepreneurship literature is broadening the scope beyond founders and demonstrating early joiners as key members of initial teams. Unlike other rank-and-file employees whose human capital 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 hypothesize that the impact of initial team members stems from their contribution to the organizational capital that emerges at firm formation and becomes embodied in the initial team members. In support of this view, we find that the impact of both founders and early joiners is stronger in contexts where the role of organizational capital is expected to be heightened.

We conclude by discussing three avenues for future research. First, we find a substantial variation in the quality of initial teams' human capital as proxied by prior earnings. While the focus of this study has been on the cross-sectional differences in human capital, an important question is whether and how the human capital quality of initial teams has evolved over time. With declining dynamism (e.g., Decker et al. 2017) and rising concentration among large employers (e.g., Autor et al. 2020), a possibililty 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, what may explain 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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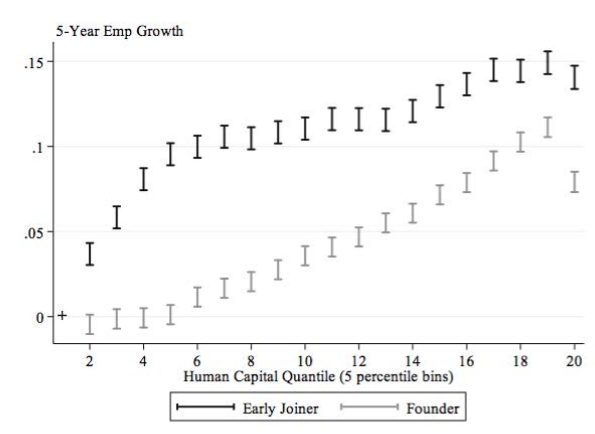
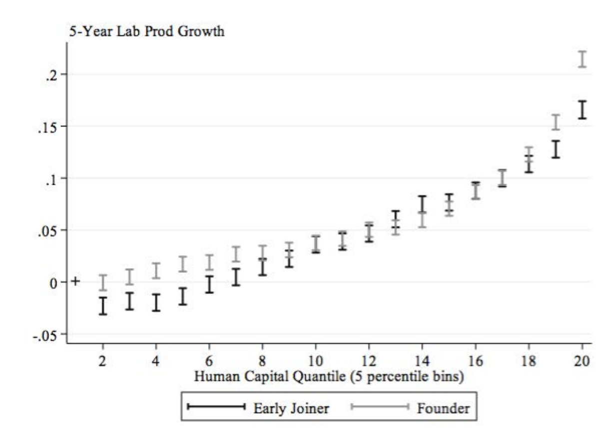
Figures

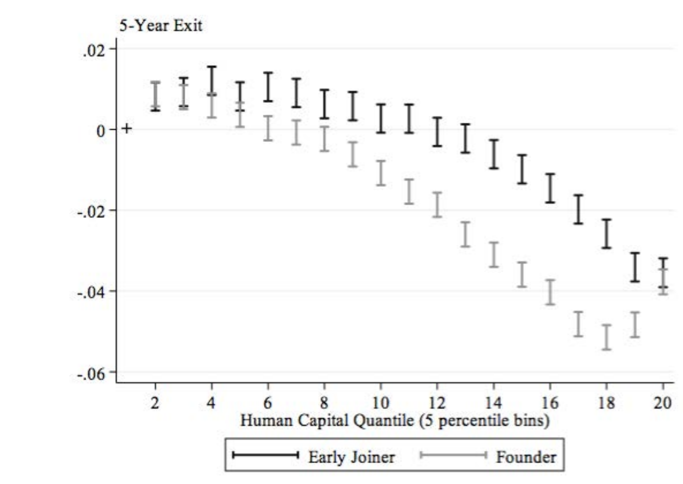
Figure 1: Founder and Early Joiner Human Capital and Startup Outcomes



(a) Emp Growth and Human Capital



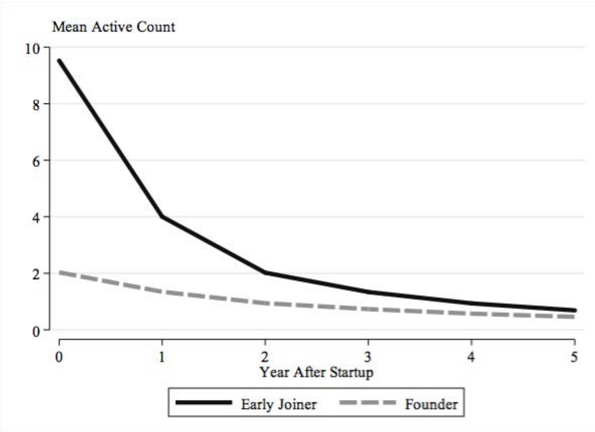
(b) Productivity Growth and Human Capital



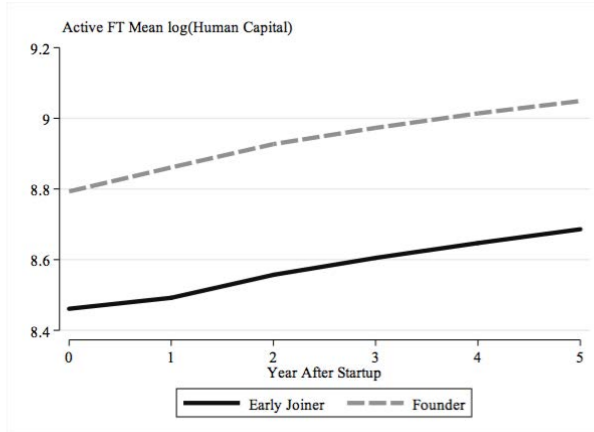
(c) Exit and Human Capital

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: 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 HC bin. Estimates are relative to reference group HC bin 1.

Figure 2: Founder and Early Joiner Attrition and Human Capital



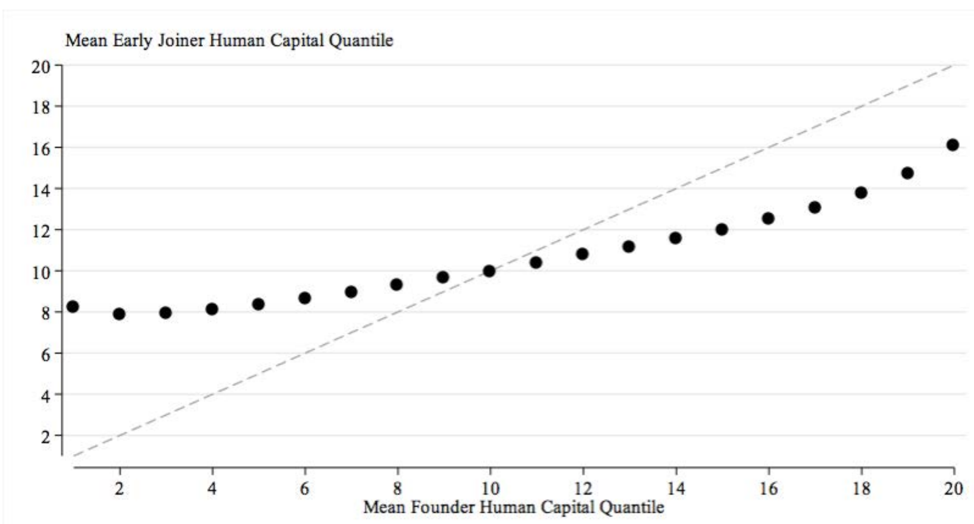
(a) Attrition of Founders, Early Joiners



(b) Human Capital of Active Founders, Early Joiners

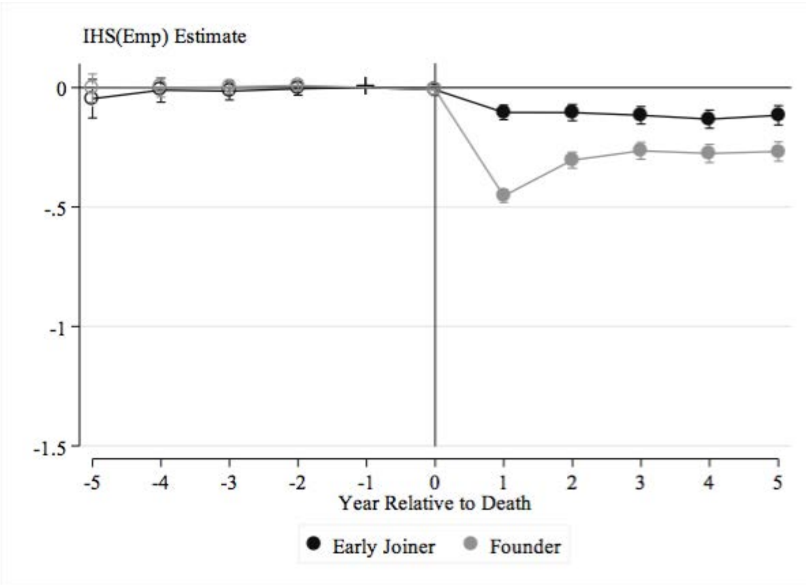
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Mean count of active (earnings positive) founders and early joiners each year after startup (a) and mean active founder and early joiner log human capital (prior earnings) (b).

Figure 3: Human Capital Composition of Founders and Early Joiners

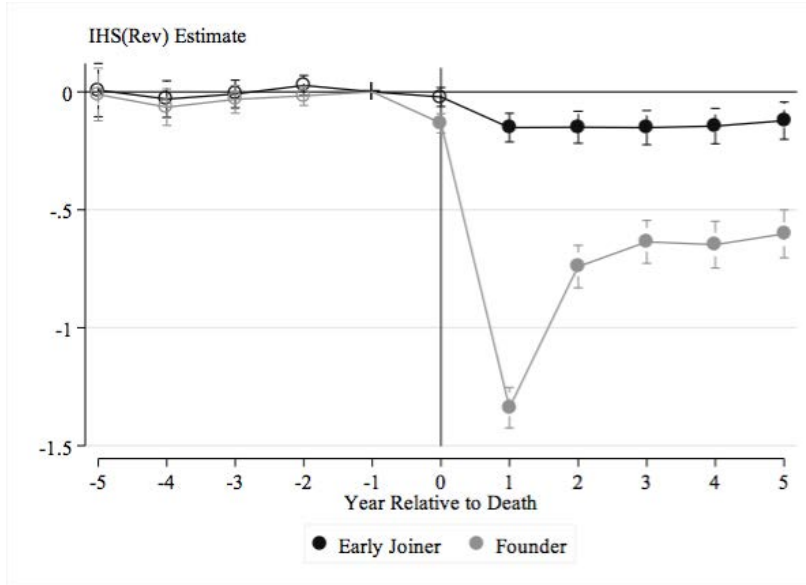


Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Mean early joiner human capital quantile bin for each founder human capital quantile bin. 45° shown to emphasis when founder human capital position is equal to early joiner human capital position.

Figure 4: Death Shocks of Founders and Early Joiners, $ihs(Emp)$ and $ihs(Rev)$



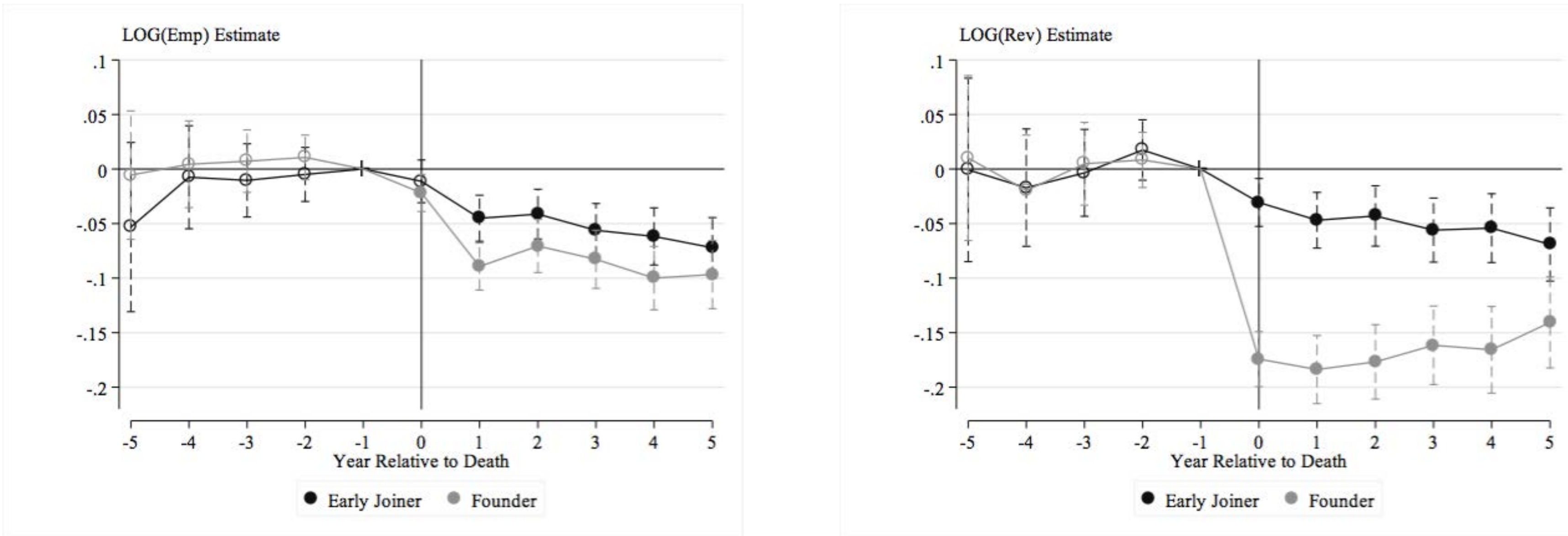
(a) Death Shocks and $ihs(Emp)$



(b) Death Shocks and $ihs(Rev)$

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 5: Death Shocks of Founders and Early Joiners, $log(Emp)$ and $log(Rev)$

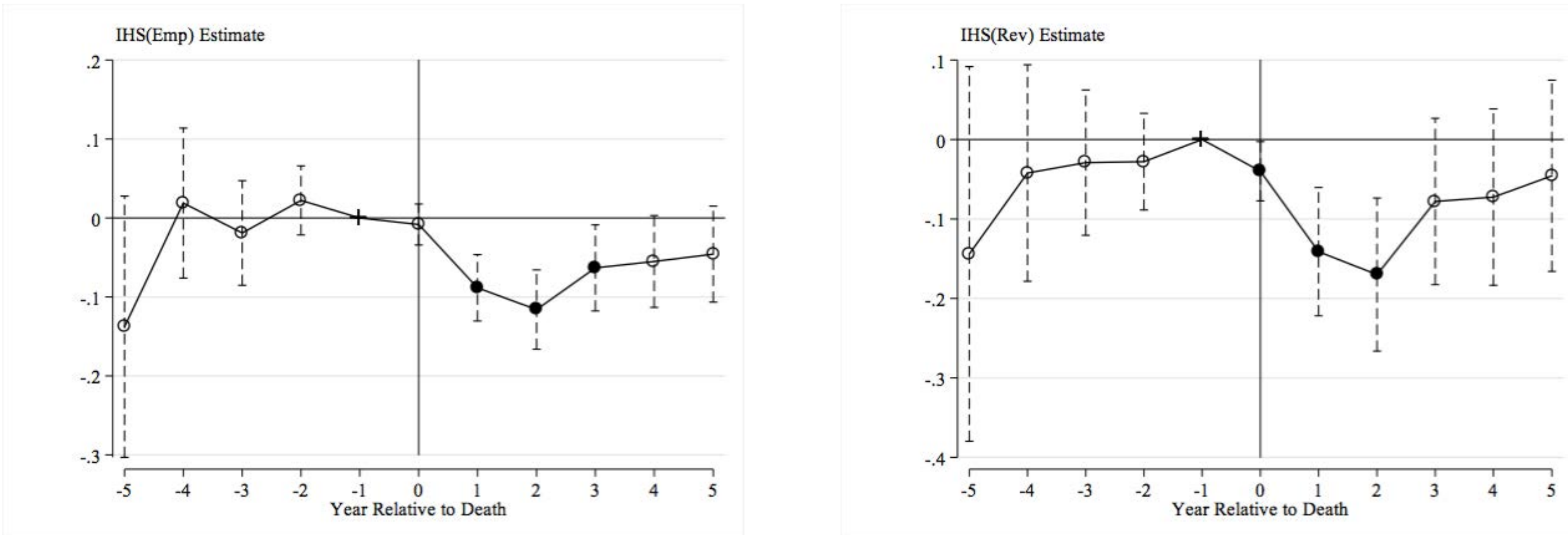


(a) Death Shocks and $log(Emp)$

(b) Death Shocks and $log(Rev)$

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 6: Death Shocks of Second Year Joiners

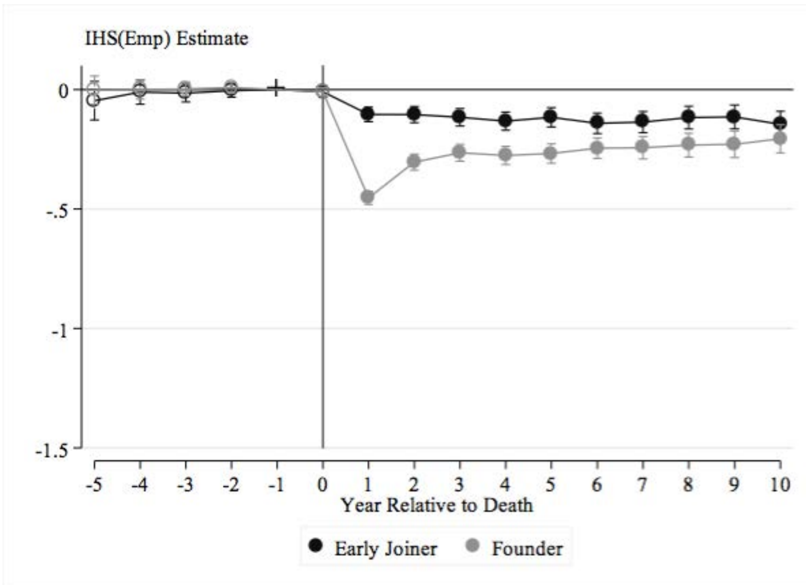


(a) Death Shocks and $ihs(Emp)$

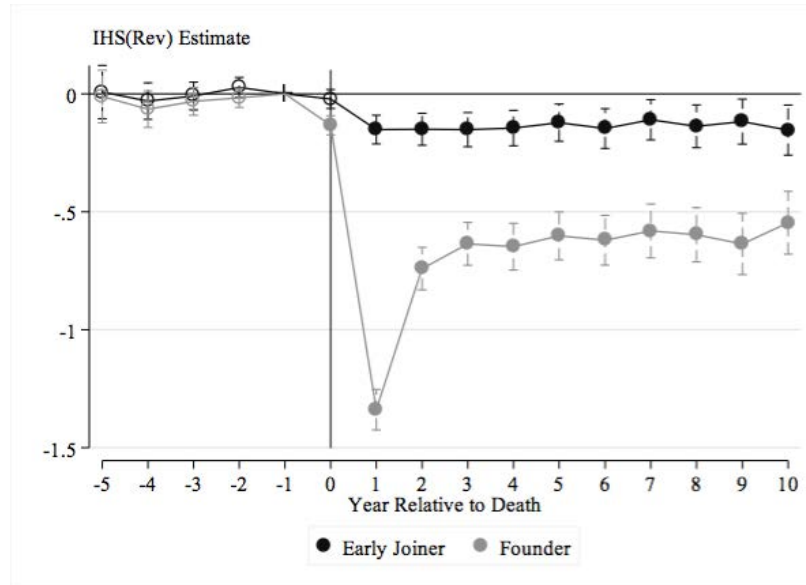
(b) Death Shocks and $ihs(Rev)$

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 7: Persistence of Death Shocks



(a) Death Shocks and $ihs(Emp)$



(b) Death Shocks and $ihs(Rev)$

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 $t-1$.

Tables

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

	Treated	Control
Firm Age	2.463	2.464
Employment	15.71	14.23
Log(Employment)	1.968	1.891
Log(Revenue)	7.166	7.161
Log(Labor Labor Productivity)	4.409	4.539
Avg Age of FT	42.05	41.98

Source: Initial Team Database (LBD, LEHD), author's calculations.
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. Observation counts rounded to avoid the disclosure of sensitive information.

Table 2: Firm Death Linear Probability Model

	Firm Dth $t+1$	Firm Dth $t+2$	Firm Dth $t+3$	Firm Dth $t+4$	Firm Dth $t+5$
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

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

Notes: Controlling for industry-year, state, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $ihs(Prod)$ indicates $ihs(Rev) - ihs(Emp)$. 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. 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 Heterogeneous Effects

	ihs(*Emp*)	*ihs*(*Rev*)	*log*(*Emp*)	*log*(*Rev*)
Post × Treated	-.08331***	-.1265***	-.03583***	-.05057***
	(.01218)	(.02323)	(.009717)	(.01207)
Post × Treated × Founder	-.1742***	-.5479***	-.03397**	-.126***
	(.01649)	(.03686)	(.01362)	(.01829)
R^2	.7161	.6024	.8767	.8918
N	316000	224000	290000	210000

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. Regression specifications also include *Post* and $Post \times Founder$, the estimates for which are excluded for simplicity.

Table 4: B2B Heterogeneous Effects

	ihs(*Emp*)	*ihs*(*Rev*)
Post × Treated	-.06108***	-.08261**
	(.01549)	(.02983)
Post × Treated × Founder	-.1697***	-.4531***
	(.02147)	(.04814)
Post × Treated × B2B	-.04855**	-.09516**
	(.02472)	(.04708)
Post × Treated × B2B × Founder	-.007533	-.1857**
	(.03332)	(.07416)
R^2	.7161	.6025
N	316000	224000

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. Regression specifications also include *Post* and $Post \times B2B$, the estimates for which are excluded for simplicity.

Table 5: Size of Initial Team

	$ihs(Emp)$	$ihs(Rev)$
Post × Treated	-.04613**	-.0688**
	(.01714)	(.02958)
Post × Treated × Founder	-.1235***	-.155**
	(.03617)	(.06761)
Post × Treated × Small	-.08243***	-.1364**
	(.02425)	(.04738)
Post × Treated × Small × Founder	-.02093	-.4086***
	(.04175)	(.08345)
R^2	.7162	.6028
N	316000	224000

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 $Post \times Small$, the estimates for which are excluded for simplicity. A firm is classified as small ($Small = 1$) if it has five or fewer active founding team members in the year of the death shock (treatment).

Table 6: Age of Firm

	$ihs(Emp)$	$ihs(Rev)$
Post × Treated	-.1398***	-.2048***
	(.018)	(.0341)
Post × Treated × Founder	-.1077***	-.4307***
	(.02335)	(.05036)
Post × Treated × Yg Firm	.05672**	.07939*
	(.02169)	(.04113)
Post × Treated × Yg Firm × Founder	-.06518**	-.116*
	(.02853)	(.06218)
R^2	.7351	.6146
N	411000	300000

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 $Post \times YgFirm$, the estimates for which are excluded for simplicity. $YgFirm$ is equal to 1 if the firm is five years old or younger in the year of treatment.

Table 7: STEM Intensive, High Tech Industries

	$ihs(Emp)$	$ihs(Rev)$
Post × Treated	-.08125***	-.1253***
	(.01234)	(.0235)
Post × Treated × Founder	-.1766***	-.5442***
	(.01671)	(.03737)
Post × Treated × HT	-.05811	-.03436
	(.07413)	(.1461)
Post × Treated × HT × Founder	.06791	-.08719
	(.09949)	(.2179)
R^2	.7161	.6024
N	316000	224000

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 $Post \times HT$, the estimates for which are excluded for simplicity. HT is equal to 1 if the firm is in a High Tech industry and zero otherwise.

Table 8: Older Initial Team Member Deaths

	ihs(Emp)	*ihs(Rev)*
Post × Treated	-.09001***	-.1327***
	(.0173)	(.03279)
Post × Treated × Founder	-.1706***	-.5334***
	(.02496)	(.05623)
Post × Treated × Old FT	.01316	.01216
	(.02438)	(.04648)
Post × Treated × Old FT × Founder	-.008061	-.0271
	(.03344)	(.07472)
R^2	.7161	.6024
N	316000	224000

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 $Post \times OldFT$, the estimates for which are excluded for simplicity. $OldFT$ 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.

Table 9: Human Capital Heterogeneous Effects

	ihs(Emp)	*ihs(Rev)*	*log(Emp)*	*log(Rev)*
Post × Treated	-.1499***	-.3133***	-.04482***	-.08924***
	(.009483)	(.0201)	(.007754)	(.01011)
Post × Treated × HC	-.2166***	-.6607***	-.0357	-.1757**
	(.04875)	(.1194)	(.04191)	(.0597)
R^2	.715	.6037	.8775	.89
N	242000	176000	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 $Post \times HC$, the estimates for which are excluded for simplicity.

Table 10: Small Business Intensive Sectors

	$ihs(Emp)$	$ihs(Rev)$
Post × Treated	-.08338***	-.1258***
	(.01461)	(.02744)
Post × Treated × Founder	-.1659***	-.5173***
	(.02063)	(.04556)
Post × Treated × HP	-.0003677	-.002745
	(.02613)	(.0514)
Post × Treated × HP × Founder	-.02113	-.08341
	(.03439)	(.07814)
R^2	.7162	.6024
N	316000	224000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry-year, firm, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $ihs(Prod)$ indicates $ihs(Rev) - ihs(Emp)$. 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.

Appendix

A.1 Model

In this appendix, we develop an illustrative two-period model of selection and size based on the formation of organizational 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 organizational 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 organizational capital. We intentionally focus initially on a specification without heterogeneity among initial team matters 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 organizational 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

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

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 organizational 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

$$\pi_{i1} = M_{i1}(1-\chi_{i1})^{\kappa}(L_{i1}^{IT} + \gamma L_{i1}^{NT} - f)^{\theta} - w_1(L_{i1}^{IT} + L_{i1}^{NT}), \tag{5}$$

where w_1 is the market wage paid to the workers in the production period.[33]

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

$$M_{i1}(1-\chi_{i1})^{\kappa}\theta(L_{i1}^{IT}+\gamma L_{i1}^{NT}-f)^{\theta-1}-w_1-\lambda=0 \tag{6}$$

$$M_{i1}(1-\chi_{i1})^{\kappa}\theta\gamma(L_{i1}^{IT}+\gamma L_{i1}^{NT}-f)^{\theta-1}-w_1=0, \tag{7}$$

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

$$L_{i1}^{IT}=(M_{i1}(1-\chi_{i1})^{\kappa}\theta/w_1)^{1/(1-\theta)}+f. \tag{8}$$

Revenues are given by

$$R_{i1}=(M_{i1}(1-\chi_{i1})^{\kappa}(M_{i1}(1-\chi_{i1})^{\kappa}\theta/w_1)^{\theta/(1-\theta)}. \tag{9}$$

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

$$R_{i1}/L_{i1}^{IT}=(w_1/\theta)(1-f/L_{i1}^{IT}). \tag{10}$$

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

$$\pi_{i1}=L_{i1}^{IT}(w_1(1/\theta-1))-fw_1/\theta. \tag{11}$$

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

$$L_{i1}^{NT}=\frac{1}{\gamma}[(M_{i1}(1-\chi_{i1})^{\kappa}\theta\gamma/w_1)^{1/(1-\theta)}+f-(1-\chi_{i1})N]. \tag{12}$$

[33] 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.

Revenue is given by

$$R_{i1} = (M_{i1}(1-\chi_{i1})^{\kappa}(M_{i1}(1-\chi_{i1})^{\kappa}\theta\gamma/w_1)^{\theta/(1-\theta)}. \tag{13}$$

Revenue labor productivity is given by

$$R_{it}/L_{i1}^{tot} = (w_1/\theta)(1 - f/L_{i1}^{tot}), \tag{14}$$

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

$$\pi_{i1} = L_{i1}^{tot}(w_1(1/\theta - 1)) - fw_1/\theta. \tag{15}$$

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 organizational 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

$$\int\int max(\pi_{i1}, 0)g(M_{i1})h(\chi_{i1})dM_{i1}d\chi_{i1} - w_0 N = 0, \tag{16}$$

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 organizational 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 organizational 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 organizational 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

$$R_{i1} = TFPQ_{i1}(L_{i1}^{IT} + \gamma_{EJ}L_{i1}^{EJ} + \gamma_{NT}L_{i1}^{NT} - f)^{\theta}. \tag{17}$$

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).

A.2 Additional Tables

Table A1: Labor Productivity, Survival, and Growth

	Exit	EmpGrowth
$LOG(Prod)_{t-1}$	-.06402***	.2255***
	(.0000855)	(.000191)
Cons	.3993***	-1.234***
	(.0004215)	(.0009191)
Industry-Year FE	Y	Y
R^2	.05387	.1021
N	22200000	22200000

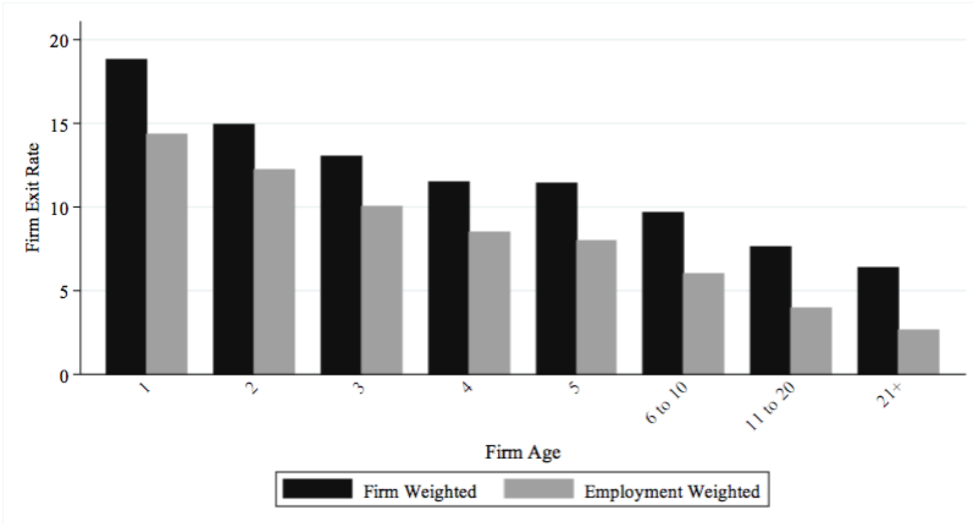
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information.

Table A2: Pre-treatment Growth of Surviving Firms

	Employment	Revenue	Labor Productivity
Treated	.007251	.00189	-.00159
	(.006282)	(.006259)	(.007477)
NAICS4 FE	Y	Y	Y
Birth Yr FE	Y	Y	Y
Firm Age FE	Y	Y	Y
R^2	.07916	.102	.0205
N	20500	14000	14000

Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for industry, cohort, and firm age effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $ihs(Prod)$ indicates $ihs(Rev) - ihs(Emp)$. Observation counts rounded to avoid the disclosure of sensitive information. Employment and Revenue show the change in Employment and Revenue between firm birth and the year prior to the premature death, respectively. Labor productivity shows the same for revenue per worker.

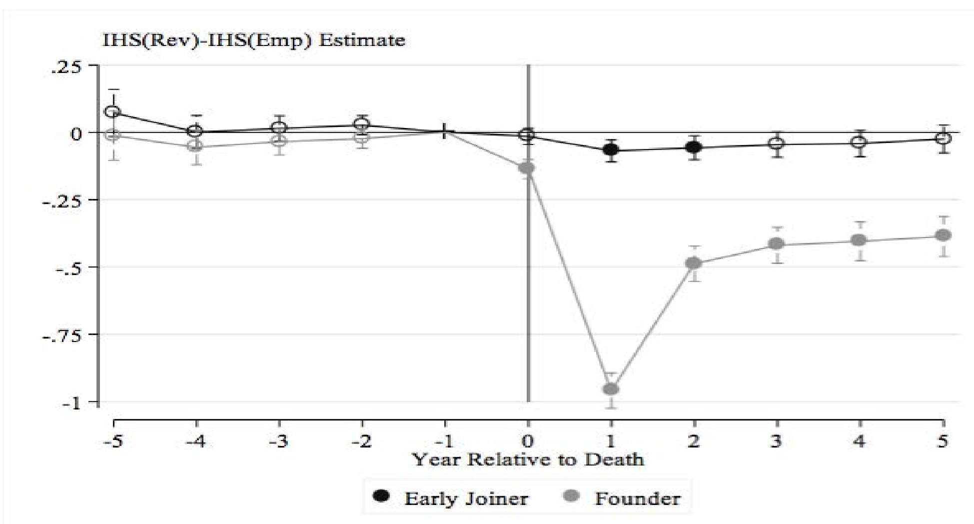
Figure A1: Firm Exit Rates and Firm Age



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

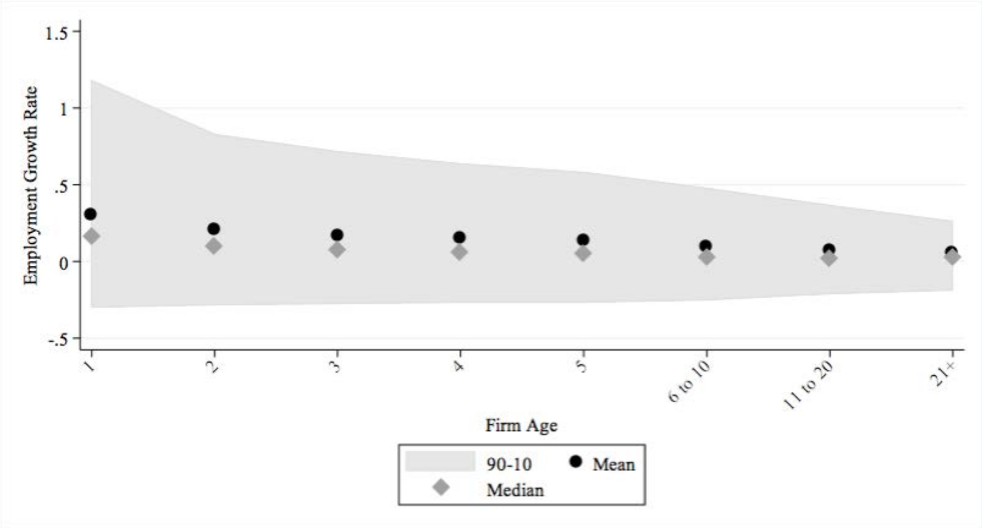
A.3 Additional Figures

Figure A4: Initial Teams Death Shocks and $ihs(Emp) - ihs(Rev)$



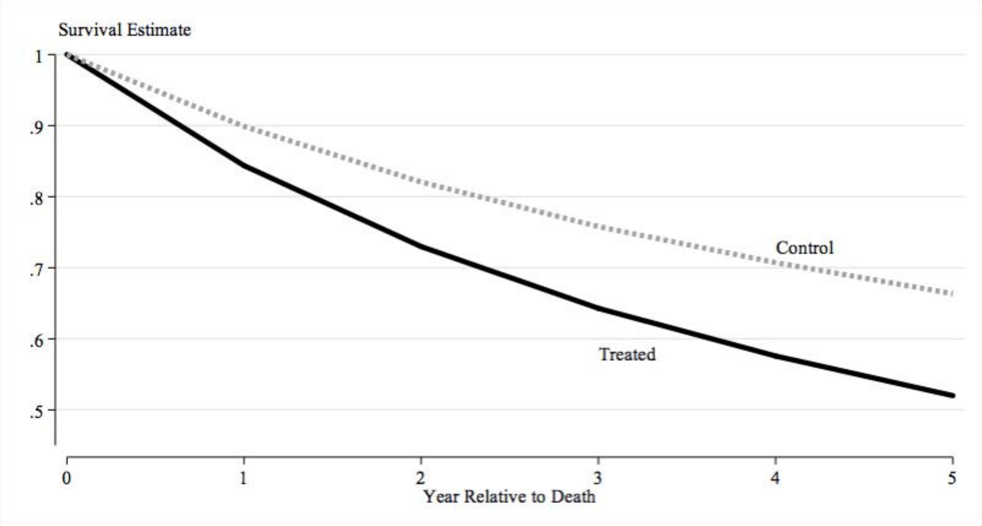
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for firm effects, firm age and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group $t-1$. Points shifted around time periods, early joiner left and founder right, to ease interpretation.

Figure A2: Firm Age and Employment Growth



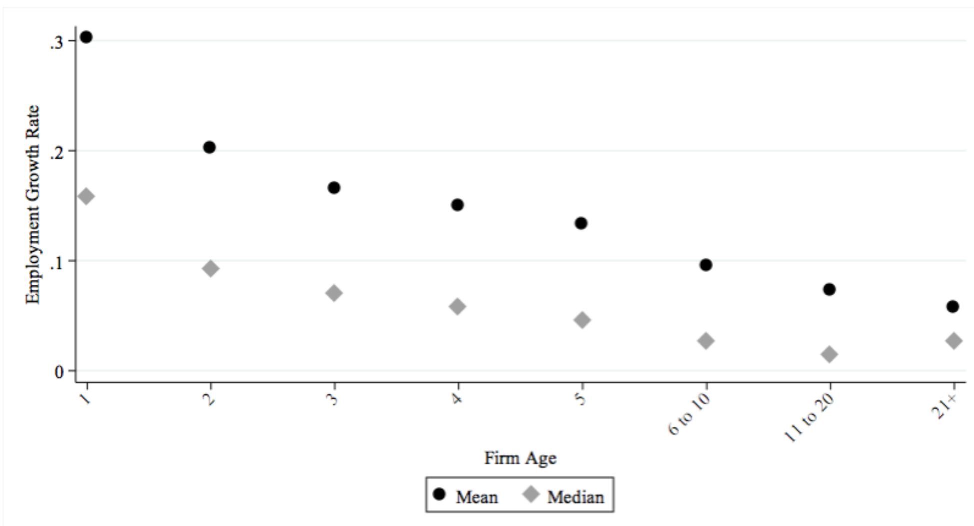
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Employment-weighted distribution.

Figure A5: Initial Team Death Shocks and Cox Survival Estimates



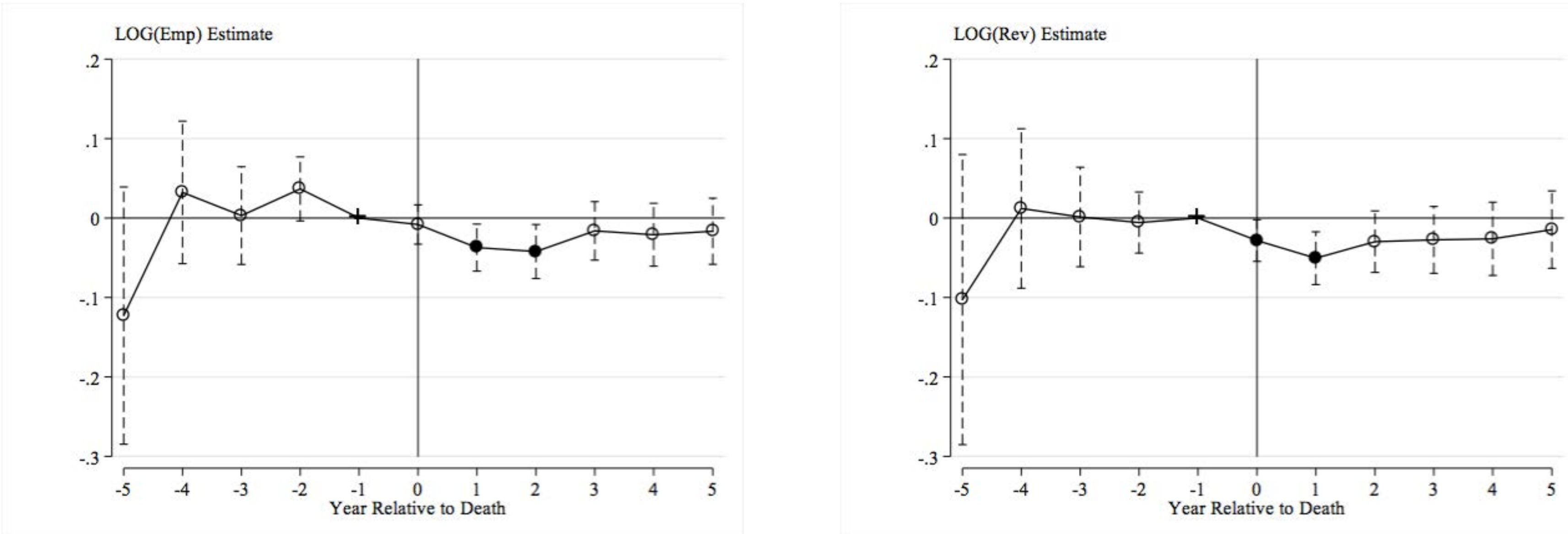
Source: Initial Team Database (LBD, LEHD), author's calculations.
Notes: Cox estimate 0.35 (0.013). Controlling for firm age, industry, state, and year.

Figure A3: Firm Age and Mean and Median Employment Growth



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

Figure A6: Death Shocks of Second Year Joiners, *log* Outcomes



(a) Death Shocks and $ln(Emp)$

(b) Death Shocks and $ln(Rev)$

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 $t-1$.

Not intended for publication.