Founding Teams and Startup Performance[*]

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Abstract

We explore the role of founding teams in accounting for the post-entry dynamics of startups. While the entrepreneurship literature has largely focused on business founders, we broaden this view by considering founding teams, which include both the founders and the initial employees in the first year of operations. We investigate the idea that the success of a startup may derive from the organizational capital that is created at firm formation and is inalienable from the founding team itself. To test this hypothesis, we exploit premature deaths to identify the causal impact of losing a founding team member on startup performance. We find that the exogenous separation of a founding team member due to premature death has a persistently large, negative, and statistically significant impact on post-entry size, survival, and productivity of startups. While we find that the loss of a key founding team member (e.g. founders) has an especially large adverse effect, the loss of a non-key founding team member still has a significant adverse effect, lending support to our inclusive definition of founding teams. Furthermore, we find that the effects are particularly strong for small founding teams but are not driven by activity in small business-intensive or High Tech industries.

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Startups and young firms contribute disproportionately to job creation, innovation and productivity growth (Haltiwanger, Jarmin, and Miranda, 2013; Decker, Haltiwanger, Jarmin, and Miranda, 2014; Acemoglu, Akcigit, Bloom, and Kerr, 2018). A hallmark of young firm dynamics is the enormous dispersion in outcomes. Most startups fail in their first five years but conditional on survival, young firms grow faster than their more mature counterparts. Amongst survivors, there is tremendous dispersion in post-entry growth rates. While most of the contribution by young firms to aggregate employment and output growth can be attributed to survivors that grow rapidly, relatively little is known about the sources of heterogeneity across young firms that generate up-or-out dynamics. In this paper, we combine data on new business starts and their founding teams to characterize the relationship between founding teams and young firm dynamics. While the existing entrepreneurship literature has almost exclusively focused on founders–partly due to data limitations–we broaden this view to focus on teams that include both the founders (i.e., active business owners in the first year of operations) and initial employees in the first year of operations of the firm. After examining some basic facts about the relationship between young firm outcomes and founding teams, we use premature death shocks to identify the causal effect of an exogenous separation of a founding team member on firm performance. Moreover, we explore heterogeneous treatment effects based on the characteristics of the founding team members as well as the characteristics of the firms.

We integrate administrative employee-employer payroll data with administrative tax information covering non-farm employer startups between 1990 and 2015 for a large sample of U.S. states. We focus on employer startups that organize themselves as sole proprietors or corporations where we can capture active business owners and other members of the founding team. Founding teams are identified as all workers with positive earnings in the first year after startup supplemented by business owners of sole proprietors. Using each founding team member's most recent earnings prior to joining the startup as a proxy for human capital, we document new stylized facts about the relationship between human capital

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composition of founding teams and startup performance. Since the effects of the founding team may be concentrated among certain individuals, we decompose the founding team into two groups: key founding team members (KFT) and non-key founding team members (Non-KFT). Key founding team members are identified as the founding team members with the highest earnings at the firm and for some firms the business owner.[1] This measure flexibly captures individuals holding key positions in the firm, whether or not they have a financial stake in the firm. We examine the relationship between the human capital composition of the founding team, among both KFT and non-KFT, and firm outcomes including size and productivity, growth, and survival. We also explore the attrition of founding team members–the number of founding team members that still work for the firm each year after founding. We find that firms with high human capital founding teams are more likely to survive and grow in terms of scale (employment and revenue) and labor productivity. These patterns hold despite significant attrition of founding team members. Attrition is lower for KFT and higher human capital members of the founding team.

These patterns provide a richer portrait of young firm heterogeneity, but a number of endogeneity issues complicate the link between founding teams and firm outcomes. There may be factors that are systematically related to both the characteristics of the founding team and startup performance. For example, high-ability individuals may be more likely to join ventures based on ideas or technology with greater market potential. Therefore, the positive relationship between founding team's human capital and firm outcomes could be driven by unobserved characteristics (e.g., quality of underlying business idea) that are endogenously tied to the characteristics of the founding team.

This empirical challenge has been at the center of a debate in the entrepreneurship literature regarding the relative importance of the firm (horse) versus the founders (jockey) (or interpreted more broadly the founding team). For instance, Kaplan, Sensoy, and Strömberg

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[1]For sole proprietorships we identify the business owner through tax filings, in which case we include the business owner in the key founding team group. For corporations, we include the three top earners. Kerr and Kerr (2016) and (Azoulay, Jones, Kim, and Miranda, 2018) present evidence that these likely include active business owners of corporations.

(2009) study a sample of 50 venture capital-backed firms and document that the core business ideas tend to be much more stable than the founding team, suggesting the importance of the horse over the jockey. Consistent with this view, although the founding team may be critical to the earliest stages of launching a venture, they may not have the appropriate skills to build and grow the business (Wasserman, 2017; Kulchina and Gjerlov-Juel, 2019). More generally, founding teams may be less critical after a business idea has been sufficiently developed, at which point the founding team members could be replaced by individuals with suitable skills. This perspective implies that losing a founding team member would have little to no persistent effect on the post-entry dynamics of the firm.

Alternatively, the loss of a founding team member may result in a much more adverse impact. In the early periods of new businesses, the founding team is actively engaged in the formation of organizational capital that may be inalienable from the team itself. This includes the many factors that differentiate businesses including the core business vision, customer and supplier relationships, reputational capital, and business norms and culture. Such organizational capital likely grows as the founding team members work together and develop team-specific complementarities. Therefore, losing a founding team member results in the loss of accumulated organizational capital and the dissolution of those team-specific complementarities. Under this alternative view, the loss of a founding team member may have a profound and persistent impact on firm outcomes.

To address these issues with causal inference, we leverage the premature death of a founding team member as an exogenous separation.[2] Specifically, we use a difference-in-difference framework to compare outcomes of "treated" firms that experienced the death of a founding team member to a group of matched control firms that did not. We use a coarsened exact matching procedure to find control firms within the same industry, state, legal form of organization, and year of startup and that have similar characteristics such as size and average age of the founding team. Our matching procedure is able to generate

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[2]As we discuss below, our identification approach builds on a recent literature using premature deaths for treated vs. control firms as reflecting plausibly exogenous variation.

parallel and statistically indifferent pre-shock trends in outcome variables. We measure the dynamic response to the premature death shock by comparing the employment, revenue, and labor productivity of treated and control firms. We find that the premature death of a founding team member has a large, negative, and persistent impact on the scale and productivity of the firm. Five years after the event, employment, revenue and productivity are about 16, 32 and 17 log points lower than their pre-event levels, respectively. We also find that losing a founding team member lowers the probability of survival.

Next, we investigate heterogeneous treatment effects to better understand when and how premature death negatively impacts the firm. First, we assess how the effect varies by the deceased individual's relative standing in the firm - specifically, KFT versus non-KFT. Perhaps unsurprisingly, the negative impact from premature death is much larger when occurring among KFT. Nonetheless, the effect is significantly negative and persistent even when the deceased person is a non-KFT. We find a similar pattern for the human capital of the founding team member. The loss of a high human capital founding team member has a significant, negative impact on the firm, but even losing an average human capital team member affects the firm. Taken together, our findings highlight that organizational capital is collectively embodied in the entire founding team, though it is disproportionately captured by the key founding team members.

We also explore differential effects based upon the characteristics of the firm. First, we investigate whether the adverse impact of losing a founding team member is more pronounced for small founding teams. We find that the effect is larger for small (five or less) founding teams, while a smaller, but still statistically significant effect is found for larger teams. Second, we explore whether the effect of losing a founding team member varies by sector. To that end, consider two informative extremes: small business-intensive and High Tech industries.

One hypothesis is that the effects we observe are driven by startups in small business-intensive sectors as in Hurst and Pugsley (2011) (e.g., plumbers, skilled-craftsmen), where

founders are more likely to have non-pecuniary benefits from being a small business owner. In such sectors, the majority of the business profit is likely generated by the business owners' human capital. Thus, for these types of startups, we might expect the loss of a founding team member to have a greater impact. However, we do not find statistically differential effects for firms in small business intensive sectors, although the estimated effects are slightly larger in magnitude when we restrict the sample to this sector only. Therefore, we reject the null that our main effects are mostly driven by small business intensive sectors.

Alternatively, the loss of a founding team member might be especially important in innovation-intensive industries. In such industries, organizational capital that embodies the core novel business idea may be especially important. We find that the impact in High Tech sectors of losing a founding team member is about the same as other sectors.[3]

Our work contributes to both the new ventures and firm dynamics literatures. First, there are several strands of the new ventures literature focused on the determinants of startup success. Canonical firm dynamics models cite heterogeneity in initial technical efficiency endowments as the key driver of up-or-out dynamics of young firms (e.g. Jovanovic (1982)). The empirical literature has identified a number of initial characteristics that correlate with firm outcomes including age of the workers (Ouimet and Zarutskie, 2014), the outside options for and age of the founders (Choi, 2017; Azoulay, Jones, Kim, and Miranda, 2018), the name or the incorporation location of the business (Guzman and Stern, 2015), and ex ante firm heterogeneity more broadly (Pugsley, Sedlacek, and Sterk, 2018). Founders may be particularly important for firm outcomes because of their central role in business decisions. Studies of firm founders tend to stress the importance of human capital (Lazear, 2004) and risk tolerance (Iyigun and Owen, 1998). There is also a growing body of evidence that founding teams play an important role in firm success.[4]

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[3]We identify High Tech industries based upon their relative share of Science, Technology, Engineering, and Math workers using the classification developed by Goldschlag and Miranda (2016), which is based upon the work of Hecker (2005).

[4]For example, Agarwal, Braguinsky, and Ohyama (2019) stress the importance of stable shared leadership of the top management team. See Klotz, Hmieleski, Bradley, and Busenitz (2014) for a review.

Venture capital and private equity studies have explored the relative importance of founders and founding teams (Kaplan, Sensoy, and Strömberg, 2009; Ewens and Marx, 2017). We build upon these studies by establishing new facts about the relationship between founding team human capital and firm performance with a sample that covers the majority of new businesses in the U.S.–moving well beyond the samples of venture backed startups typical of the literature. Moreover, the scale of the data allows us to leverage a relatively rare event, premature death of active founding team members, to introduce causal estimates of the impact of founding team members.

Our work also builds upon the entrepreneurship and firm dynamics literature. As noted previously, several empirical studies have documented the importance of firm entry and young firms in aggregate job creation and productivity dynamics (Haltiwanger, Jarmin, and Miranda, 2013; Alon, Berger, Dent, and Pugsley, 2018; Decker, Haltiwanger, Jarmin, and Miranda, 2016). We contribute to this literature by providing new stylized facts about the relationship between founding teams, initial human capital composition, and young firm dynamics. Our findings paint a much richer portrait of the initial conditions of successful startups and how the evolution of human capital within young firms contributes to survival and growth.

Closest to our work is a recent study by Smith, Yagan, Zidar, and Zwick (forthcoming) (henceforth SYZZ), which explores the importance of human capital of firm founders using premature death for identification. SYZZ focus on closely-held pass-through businesses (i.e., S-corps and partnerships) with wealthy owners (at least a million dollars in fiscal income) and examines the impact of premature deaths on profits per worker using a broadly similar identification strategy.[5] SYZZ find large adverse effects on profit per worker that persist for at least four years. There are several key distinctions between their analysis and ours. For one, we focus on all young businesses inclusive of sole proprietors and all corporations

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[5]SYZZ use the profits per (pre death number) of workers in order to be able to include non-surviving businesses in their analysis. We use the inverse hyperbolic sine measures to be inclusive of non-surviving businesses.

(not just S-corps) and we exclude partnerships.[6] In contrast, their analysis focuses on the narrower set of high income individuals who own closely held pass-through businesses. In addition, we take a broader view that includes the entire founding team. Finally, while SYZZ place their work in the context of income distribution dynamics of top income earners , while our work focuses on young firm dynamics.[7]

The paper is organized as follows. We sketch an illustrative motivating model in 1 that helps clarify the role of organizational capital and it being embodied in the founding team. We discuss our data infrastructure in sections 2. Section 3 describes basic facts about the post-entry dynamics of startups and the relationship of these dynamics to the characteristics of founding teams. Section 4 presents our identification methodology using premature deaths, our main results and then analysis of heterogeneous treatment effects. Section 5 concludes.

1   An Illustrative Model

In a standard model of entry, selection, and growth, 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 lower draws are smaller, and those with sufficiently low draws exit due to their inability to cover fixed costs. The standard model

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[6]As we explain below, active or managing owners of partnerships file Schedule K-1 pass-through income that we are unable to observe in our data. Therefore, we exclude them from our analyses. SYZZ uses data from the U.S. Treasury Department, which has both advantages and disadvantages. An advantage of those data is the comprehensive coverage of owners via the K-1 data. A disadvantage is the definition and longitudinal tracking of firms. We use the enterprise firm identifiers in the Census LBD capturing operational control, which allows firm exit to be defined as all establishments that operated under that firm identifier ceasing operations. In contrast, the Treasury data uses taxpayer IDs to define a firm, which complicates tracking the firm over time because EINs change for many reasons including change of owner. They use some clustered flow of workers analysis to overcome this issue. Also, many firms use multiple EINs so a taxpayer ID definition of the firm is limited.

[7]A related study by Becker and Hvide (2019) investigates the impact of losing founders 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. As with SYZZ, a critical distinction between our work and theirs (in addition to the distinction between results for the U.S. versus Norway) is our broader interest in all founding team members. Relatedly we examine heterogeneous treatment effects by founding team member characteristics as well as by firm type to draw out the broader implications of all founding team members.

(e.g. (Hopenhayn, 1992)) is a dynamic, multi-period model with assumptions about the persistence of stochastic productivity draws as well as sources of dynamic adjustment such as adjustment costs or learning. However, the essence of the model can be captured in a stylized ex ante, ex post representation. Lucas (1978) is an example of the latter where the ex post productivity draw is entrepreneurial ability where the entrepreneurs learn their ability after paying their fixed cost.

We build on this simple ex ante, ex post representation with an illustrative two period model of selection and size based on the formation of organizational capital by founding teams. To start a business, an entrant pays a fixed entry fee in a formation period with a founding team devoting time and resources to develop organizational capital. Let the number of founding team members be given by N. Founding 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 ex ante differences among founding team matters to highlight the potential role of the founding team even without such effects. We discuss extensions with ex ante heterogeneity below.

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

available as employees in the production phase period 1 is $L_{i1}^{FT} \leq (1 - \chi_{i1}) N$. Thus, the maximum share of founding 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:

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

where L_{i1}^{NT} is the number of non-founding 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-founding 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 founding team members always exceeds that of non-founding team members as long as $\gamma < 1$.[8]

The profit function is given by:

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

where w_1 is the market wage paid to the workers in the production period.[9]

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

$$L_{i1}^{NT} = \frac{1}{\gamma}[(M_{i1}(1 - \chi_{i1})^{\kappa}\theta\gamma/w_1)^{1/(1-\theta)} + f - (1 - \chi_{i1})N] \qquad (3)$$

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[8]This formulation does not have any knowledge capital decay from endogenous attrition of founding team members. Adding this feature enhances the results discussed below but yields less transparent decision rules. In this more general case, founding team members have higher marginal revenue products than non-founding team members from this extra effect on productivity.

[9]Since FT members are more productive, it might be that the surplus is shared between the firm and founding team members. We assume for simplicity that the firm gets all the surplus.

Revenue is given by:

$$R_{i1} = (M_{i1}(1 - \chi_{i1})^{\kappa}(M_{i1}(1 - \chi_{i1})^{\kappa}\theta\gamma/w_1)^{\theta/(1-\theta)} \tag{4}$$

Revenue labor productivity is given by:

$$R_{it}/L_{i1}^{tot} = (w_1/\theta)(1 - f/L_{i1}^{tot}) \tag{5}$$

where $L_{i1}^{tot} = L_{i1}^{FT} + L_{i1}^{NT}$. 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. Profits are given by:

$$\pi_{i1} = L_{i1}^{tot}(w_1(1/\theta - 1)) - fw_1/\theta \tag{6}$$

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 that the constraint on the number of founding team members will be more likely to bind, which provides some incentive to replace them in production with non-founding 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} depends on $\kappa > 0$. Attrition of the founding team matters for employment, revenue, productivity and exit only if the organizational capital knowledge is embodied in the founding team members. In the appendix, we show that these implications also hold for the range when only founding team members are employed.

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

$$\int \int max(\pi_{i1}, 0)g(M_{i1})h(\chi_{i1})dM_{i1}d\chi_{i1} - w_0N = 0 \tag{7}$$

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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 founding team. The ex post productivity realizations depend on the stochastic success of the founding team and the exogenous attrition of the founding 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 founding team members.

We consider extensions of the model to allow heterogeneous ex ante workers and the more skilled playing a larger role in organizational capital.[10] Important special cases include, for example, the assumption that the organizational capital is only embodied in the more skilled. This would in turn imply that the predictions above regarding exogenous attrition would only apply to the more skilled. We test the hypothesis that the loss of more skilled founding team members has a greater impact.

2   Data Infrastructure

We construct a longitudinal dataset covering the majority of startups and their founding teams 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. non-farm establishments 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

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[10]See appendix.

control is the Company Organization Survey (conducted annually) and the Economic Censuses (conducted every five years). Information in the LBD include the number of employees, annual payroll, industry, age, births, and deaths of establishments and firms. We enhance this data by incorporating revenue information imported from the Business Register (BR) as in Haltiwanger, Jarmin, Kulick, and Miranda (2017). We define firm age as the age of the oldest establishment under each firm and startups are defined as firms with age zero. Our outcome variables of interest are employment, revenue, labor productivity, and survival. Labor productivity is measured as revenue per worker. Our focus is on the heterogeneity in outcomes within narrowly defined sectors so in all of our descriptive and causal analysis we control for detailed industry by year effects.

We focus our attention on sole proprietors and corporations where we can capture active business owners and other members of the founding team. We define the founding team as all individuals with positive unemployment insurance (UI) covered earnings at the startup within the firms' first year of operation and 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 Business Register. We are therefore able to combine sole proprietor owners with the founding teams recovered from the LEHD. Active or managing owners of partnerships, on the other hand, file Schedule K-1 pass-through income that will not be observed in either the Business Register or the LEHD. We therefore exclude partnerships from our startup sample.[11] 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 are required to receive employment compensation. For example, the IRS states "The definition of an employee under the Internal

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[11]In the future, we plan to explore the K-1 for robustness analysis as in hope to include partnerships using K-1 information for partnerships and S corporations, which have been linked to the LBD (Goldschlag, Kim, and McCue, 2017).

Revenue Code include 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."[12] Indeed, using K-1 and W-2 filings data, Nelson (2016) finds that almost 90% of all S corporations with paid employees have at least one shareholder-employee.[13] Furthermore, Nelson (2016) documents that privately-held C corporations "appear to pay out a majority of the owners' income in the form of executive compensation" and virtually all C corporation startups are privately held.[14] Therefore, for the vast majority of the startups in our data, our measurement methodology of founding teams is likely to capture both active business owners and the first-year joiners who are not shareholders.

We further decompose the founding team into two groups. The first group is what we referred to previously as key founding team members (KFT for short). The second group is the remainder of the founding team excluding key founding team members (non-KFT for short). We define the KFT of non-sole proprietorships to be the three workers with the highest earnings at the firm during the first year. This type of measure has been used as an approximation method for identifying firm founders for startups of certain types of legal forms (e.g, Kerr and Kerr (2016); Choi (2017); Azoulay, Jones, Kim, and Miranda (2018)). We depart from this literature and do not refer to the KFT as firm founders since it is possible that a significant share of the top three wage earners of a corporation may not be founders. However, we think it is reasonable that founders are more likely to be in KFT for corporations since Azoulay, Jones, Kim, and Miranda (2018) find that about 90% of S corporation owners identified by K-1 filings data also appear as the top three earners during

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[12]See https://www.irs.gov/businesses/small-businesses-self-employed/s-corporation-employees-shareholders-and-corporate-officers.

[13]The restriction to businesses with paid employees (our focus) is crucial. There are a large number of non-employer S-corporations. Nelson (2016) reports about 30% of all S-corporations have no employees. We exclude non-employers from our analysis.

[14]Also, see https://www.irs.gov/businesses/small-businesses-self-employed/paying-yourself which states that the "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 helps explain why some K-1 owners of S corporations do not show up in W-2 as employees. We regard such owners as passive owners of less interest to our analysis.

the firms' first year in the W-2 and LEHD data.[15] For sole proprietors, because owners are not observed in the LEHD, we define KFT as the business owner and the top two workers with the highest earnings. Our KFT therefore captures the set of workers that are likely to hold a key leadership position within the firm regardless of whether they have a financial stake in the firm. The non-KFT group is simply the remaining founding team members that are not identified as KFT.[16]

We use the prior earnings of each founding team member as a proxy for human capital, which captures heterogeneity in skills and experience. Prior earnings is computed as the individual's most recent full-quarter earnings prior to joining the startup.[17] Throughout we reference this prior earnings measure as human capital. We think it is a reasonable proxy for the latter but critically for us it is predetermined and thus a characteristic we can readily use in our heterogeneous treatment effect analysis. For our basic facts, we split each cohort of startups into 20 equally sized bins based on the average human capital of the entire founding team and the KFT and non-KFT subgroups. For the difference-in-difference premature death analysis we construct a relative human capital measure that we leverage in the heterogeneous treatments analysis. In the following section we relate average founding team, KFT, and non-KFT human capital to firm outcomes such as survival, size, growth and labor productivity. The patterns discussed in the next section are interesting in their own right but are primarily intended to provide more guidance regarding the variation in the data that we exploit later in our analysis of causal inference.

Our use of human capital of each founding team member avoids some of the challenges of identifying key founding team members via the top three earners at the firm. As we have noted, some owners of corporations are not in the top three earners of their firm but using

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[15]Note that, unlike (Nelson, 2016), Azoulay, Jones, Kim, and Miranda (2018) is based on employer startups in the LBD.

[16]It is still possible that not all active founders are in our founding team. As such, our findings of a large adverse impact of the loss of a FT member and especially a KFT member of the founding team are that much more striking.

[17]Full-quarter earnings is measured as earnings for a quarter in which the individual also was observed with earnings in the prior and subsequent quarter. These restrictions ensure the earnings measure captures an entire quarter of work rather than a partial quarter.

prior earnings offers an alternative metric to identify key members of the founding team. Comparing results for key founding team members and by human capital provides a useful cross check.

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

3   Basic Facts about Firm Outcomes and Founding 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 the 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, A3 and Table A1.

We also find systematic and statistically significant relationships between the human capital of the founding team and key outcomes. All of the results we report control for industry by year effects and include controls for initial conditions (initial size for survival and employment growth and initial productivity for productivity growth). First, we find that firms with high human capital KFT are larger (see Figure 1). For all founding team members and the non-KFT sub-group, we find an inverted U-shaped relationship between human capital and initial size. Firms at the top and bottom of the founding team human capital distribution start with relatively fewer employees. Turning to post-entry outcomes, firms with high human capital KFT and non-KFT experience higher employment growth

rates conditional on survival (Figure 2). The relationship with the founding team (FT) is similar but turns down for high human capital groups.

Conditional on survival, productivity growth increases with human capital for FT, KFT and non-KFT (see Figure 3). Firms with higher human capital founding teams are also less likely to exit (Figure 4). This pattern holds monotonically until the very top ventiles. Attrition is also significant for the FT, KFT and non-KFT groups (Figure 5). Interestingly, for FT, KFT and non-KFT groups the attrition is from the bottom of the human capital distribution. That is, conditional on survival, the average human capital of founding team members remaining at the startup increases over time. Finally, we also find evidence of substantial positive assortative matching between KFT and non-KFT subgroups (Figure 6).

In short, we find that the human capital of founding teams is closely linked to the up-or-out dynamics of young firms. However, these are only correlations since both the composition and attrition of the founding team are endogenous. To identify causal relationships, we use exogenous variation in the founding team due to premature death. We turn to that analysis now.

4   Causal Impact of Founding Teams

We use the premature death of founding team members to approximate an ideal experiment in which a founding team member is randomly separated from a startup. Our research design combines a matching strategy and a difference-in-differences framework. This approach allows us to estimate changes in startup outcomes for firms that experience a premature death among a founding team member, relative to counterfactual startup outcomes in the absence of such death. More specifically, for each startup firm that experiences a death among a founding team member in quarter t, we find a control firm that looks similar by matching on characteristics measured in the same quarter. One strength of this approach is that we can empirically test the key assumption that the treated and control firms exhibit

similar trends prior to the death shock. If the pre-shock trends are not similar, premature death is not likely to be as good as randomly assigned between the treated and control firms.

In order to focus on early-stage startups, we examine firms that experience the death of a founding team member within the first five years of the firm's operation. We then track firms for five years after the event including the possibility that the firm exits. Firm exits in the LBD occurs when all of the establishments associated with the firm cease to have employees (i.e., they do not reflect exits due to acquisitions).

Information gathered from the Census NUMIDENT file is used to identify premature deaths. Following Jaravel, Petkova, and Bell (2018) and a number of other studies that use premature death as a source of identification (e.g. Jones and Olken, 2005; Nguyen and Nielsen, 2010; Azoulay, Graff Zivin, and Wang, 2010), we classify premature death as death at or before 60 years of age. For a founding team member's death to be considered a shock to the firm, we require that the individual have positive earnings during the death shock quarter followed by zero earnings afterwards. For sole proprietor owners we measure their death as a shock to the firm only if the firm has non-zero employees in the death shock quarter and did not change its EIN since its inception.[18] Our treated firms are those with only one premature death in the first five years (and controls have no deaths).

Coarsened exact matching is used to identify a control firm for each treated firm that experienced a premature death shock (Blackwell, Iacus, King, and Porro, 2009). Specifically, 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. We also match on the number of active founding team members prior to the death shock. Whether a firm experiences a death shock is related to the number of founding team members still active at the firm. A firm with more active founding team members will have a higher probability of treatment. The probability a firm experiences the death of a founding team member is also importantly related to the age of its founding

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[18]If a business experience a change in ownership it must request a new EIN or file under some other existing EIN.

team. Therefore, we match on the average age of the active founding team members in the death shock quarter. Typically multiple control firms are matched to each treated firm after the coarsened exact matching procedure. Instead of using matching weights, we select the closest matched control firm based on the absolute differences in the continuous matching variables. Then we break ties randomly and choose only one control for each treated firm. Control firms are not selected with replacement–we do not use a matched control firm as a control for other treated firms.

Selected summary statistics for the treated and control firms are presented in Table 1 evaluated in the treatment (death shock) year. There are about 26K treated and control firms.[19] The sample is reduced for revenue based measures since the revenue enhanced LBD only covers about 80% of the LBD.[20] Treated and controls have similar firm age, founding team age, and (log) levels of employment, revenue and productivity. Importantly, these measures do not control for industry or other firm characteristics. Of more relevance, as we will see below, within firm pre-treatment trends for key outcomes are statistically indistinguishable for the treated and the controls once we have included firm effects, industry by year effects and other controls.

4.1 Main Results

The primary outcome variables of interest include scale in employment and revenue and labor productivity. Specifically, we consider the inverse hyperbolic sine (ihs) of employment, ihs of revenue, and labor productivity approximated as the difference between the ihs revenue and ihs employment.[21] By using the ihs measures we are able to include the impact of treatment

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[19]We have found that the treated-control sample has similar characteristics as the full founding team database.

[20]Haltiwanger, Jarmin, Kulick, and Miranda (2017) show that the pattern of missingness for revenue is approximately random. We will investigate this further in future drafts.

[21]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) described the advantages of the ihs transformation for analysis of distribution of outcomes with extensive zero values (e.g., earnings, wealth, employment,etc.) Variation in IHS measures are approximately equivalently to log variation for x not close to zero.

inclusive of the intensive and extensive margins. We will also consider log employment, log revenue, and log labor productivity (revenue per employee), which condition on survival. Our primary DID regression specification is as follows.

$$Y_{i,j,t} = \sum_{k=-5}^{5} \lambda_k d[k]_{i,t} + \sum_{k=-5}^{5} \delta_k d[k]_{i,t} \times TREAT_i + \alpha_i + \tau_{j,t} + \epsilon_{i,j,t} \tag{8}$$

$Y_{i,j,t}$ 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 it experiences a death of a founding team member. α_i and $\tau_{j,t}$ are firm and industry by year fixed effects. Estimates of δ_k are the parameters of interest, representing the change in the startup i's outcomes in each year relative to those of the control group. We also control for firm age fixed effect in our main specifications. Figures 7, 8 and 9 show the main results for $ihs(Emp)$, $ihs(Rev)$, and their difference (which is a proxy for log labor productivity using ihs). We first analyze the differences in scale and productivity between the treated and control firms before the premature death shock. We do not find evidence of differential pre-trends for any of the outcome variables, lending credibility to our research design around the exogenous arrival of death. This allows us to causally interpret the effects following the death shock.

The impact of losing a founding member due to premature death is immediately negative, persistent, and statistically significant. Startup employment, revenue, and labor productivity (calculated as the difference between $ihs(Rev)$ and $ihs(Emp)$) sharply diminish in the year of the founding member death. Though these negative effects slightly recover in the following year, they persist up to five years after the death shock.

In interpreting these results, we note that there might be a mechanical transitory effect on employment that is a direct result of the death. That is, it might be thought that a premature death causes at least a transitory decline of one employee until a vacancy is posted and filled. The results in Figure 7 reject this interpretation on a number of dimensions. First, Davis, Faberman, and Haltiwanger (2013) show that vacancy durations are measured in days, not

years and we find effects persistent up to five years after the death shock. Second, we can quantify how large the initial transitory impact driven by the mechanical effect might be. The average size firm at the time of the death shock is 15.5 which permits us to compute the implied mechanical reduction in employment. The reduction in $ihs(Emp)$ using the mechanical effect is -0.07. This is less than half of the actual impact in period 1 after the death shock which is -0.25. Moreover, as emphasized, this mechanical effect should be transitory.

The persistent reduction in revenue is even greater than the reduction in employment. For revenue, $ihs(Rev)$ declines by 0.6 in the first year while $ihs(Emp)$ falls by 0.25. After period 1, $ihs(Rev)$ declines by about 0.4 persistently for years 2 through 5 after the death shock while $ihs(Emp)$ declines by about 0.2. The implication is that an index of productivity given by the difference between ihs revenue and ihs employment, which again is inclusive of exits, declines by about 0.4 in period 1 and 0.2 in years 2 to 5 after the death shock.

This specification using ihs, which includes the firm-year observations with zero values, reflects effects at both the extensive and intensive margins given its inclusion of the exiting firms. Given that the loss of a founding team member likely influences the likelihood of both exit and growth of the firm, we distinguish these effects. Specifically, we investigate how the death shock affects startup firms on the extensive margin (i.e., firm exit) by using a Cox proportional hazards model to assess the differences in the likelihood of survival in the years following the death event between treated and control firms. In Figure 10, we find that treated firms are more likely to exit after experiencing the death shock. Five years after the event, the likelihood of survival is more than 10 points lower for the treated compared to the controls.[22]

To further investigate the intensive margin for continuing firms, we estimate the specifications using $\log(Emp)$, $\log(Rev)$, and $\log(Prod)$ (revenue per worker) as dependent variables.

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[22]In the Cox proportional hazards model, we are comparing treated to controls using our matched sample but we don't have additional controls such as industry by year effects and firm age effects as in our analysis of the ihs results. In future drafts, we plan on estimating models of the probability of exit with these additional controls.

These measures by construction condition on surviving firms.[23]. Results are presented in Figures 11, 12, and 13. The patterns for the log based outcomes are very similar qualitatively to those for the *ihs* based outcomes. We find evidence of large, negative, persistent, and statistically significant effects of losing a founding team member on $\log(Emp)$, $\log(Rev)$ and $\log(Prod)$. The magnitude of the effects are less severe relative to Figures 7, 8 and 9 but still quantitatively large. $\log(Rev)$ declines by about 10 log points, log employment by 5 log points with an accompanying decline in productivity by about 5 log points. As with the *ihs* outcomes the effects are highly persistent. The evidence is not consistent with a transitory effect deriving either from a mechanical vacancy creation or from a temporary disruption effect.

For the log outcome results, there is a potential concern for selection bias since we are conditioning on positive activity in the post-treatment years. Conditioning on survival increases outcomes such as size and productivity for both treated and control firms. If the difference in this increase between treated and controls is negligible then selection bias is not a concern. If present, the selection bias arguably induces an understatement of our log outcome results. Our findings above show that a premature death yields an increase in the likelihood of firm exit. If the firms that exit due to premature death tend to be small (in terms of employment or revenue) and have low productivity, then this leads to a positive composition bias of treated relative to controls. In this case, the impact of premature death on size and productivity would be upward biased. Given the likely direction of the bias, we are less concerned that our finding of the adverse effects using $log(x)$ is partly driven by conditioning on survival.[24]

To explore these issues further, we compute counterfactual estimates of the impact on $ihs(x)$ in year 1 if only the extensive margin is impacted. A property we use for this purpose is $ihs(x) = prob(x > 0) * ihs(x|x > 0)$. In year 1, according to Figure 10, the probability of

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[23]Note that treated and control firms exist at the time of the shock. No exit occurs prior to death shock among either treated or control firms.

[24]In future drafts, we plan to estimate the *log* specifications with a selection correction.

survival is about 0.04 less for treated compared to controls. Using this difference, we find that the counterfactual estimate for $ihs(Emp)$ is -0.11 in year 1, while the actual estimate from Figure 7 is -0.25.[25] The difference between the actual and the counterfactual estimate is -0.14. This difference can be interpreted as reflecting a measure of the ihs impact not accounted for by the extensive margin. The counterfactual estimate for $ihs(Rev)$ is -0.29 which differs from the actual estimate by -0.33. For $ihs(Rev) - ihs(Emp)$, the counterfactual estimate is -0.18, and the difference withthe actual is -0.24. In all cases, the differences are larger than the counterfactual estimates themselves suggesting that the extensive margin accounts for less than half of the estimated ihs effects. These differences are also substantially larger in magnitude than the log results consistent with the latter lower bound estimates of the impact on the intensive margin.

4.2   Heterogeneous Treatment Effects

To provide further guidance as to the mechanisms underlying the baseline results, we investigate a wide range of heterogeneous treatment effects. The full range of specifications we consider for heterogeneous treatment effects yields a large number of coefficients. To aid the exposition we report the results of a simplified specification that compares the differences in outcomes in the post-shock period relative to the pre-shock period. In order to help interpret the results, we first report the results of the main effects for treatment using the pre/post period specification without heterogeneity interaction terms (i.e., with homogeneous treatment effects) as follows.

$$Y_{i,j,t} = \lambda \cdot POST_{i,t} + \delta \cdot POST_{i,t} \times TREAT_i + \alpha_i + \tau_{j,t} + \epsilon_{i,j,t} \tag{9}$$

$Y_{i,j,t}$ 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

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[25]We also require estimates of $ihs(x|x > 0)$ if it was not impacted. For this purpose, we use the estimates of $ihs(x|x > 0)$ just before the death shock for treated firms. For $ihs(Emp)$ this is 2.7, for $ihs(Rev)$ this is 7.1, and for $ihs(Rev) - ihs(Emp)$ this is 4.4.

and $\tau_{j,t}$ are identically defined as in equation (8). We also control for firm age fixed effect. δ is the coefficient of interest.

Results for the pre-post main effects without interactions are reported in Table 2. The findings for this more parsimonious specification are consistent with Figures 7-9 and 11-13. The loss of a FT member yields a negative and statistically significant decline in the post period (over the five years after death shock) employment, revenue and productivity. This is true for both the extensive and intensive margins captured by the *ihs* measures and among survivors in the log measures. These estimates do not directly demonstrate the persistence of the effects as in our results above. However, the post effect is the average effect over the five year period following the death shock. As such, the results are consistent with a persistent effect. Moreover, the magnitude of the effects reported in Table 2 are broadly consistent with what one would expect by computing the average of the results over the five years post death shock from Figures 7-9 and 11-13.

To analyze the heterogeneous treatment effects, we consider an extension of our main specification as follows.

$$
\begin{aligned}
Y_{i,j,t} =& \lambda \cdot POST_{i,t} + \delta \cdot POST_{i,t} \times TREAT_i \\
& + \beta \cdot POST_{i,t} \times TREAT_i \times Z_i \\
& + \eta \cdot POST_{i,t} \times Z_i + \alpha_i + \tau_{j,t} + \epsilon_{i,j,t}
\end{aligned}
\tag{10}
$$

Z_i is the heterogeneity variables of interest that are discussed below, and the remaining variables are defined as same as before.[26]

To begin, we investigate whether the impact of losing a FT member from premature death varies with the characteristics of the person. Specifically, we examine the differential adverse impact of death of a KFT versus non-KFT and a high human capital versus the

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[26]We don't include Z_i as a separate control since it is not identified given the firm fixed effects.

average human capital founding team member. Our proxy for human capital, as described previously, is based on the prior earnings of the FT member. We construct a relative human capital measure as described below.

First, we show the results where Z_i is the KFT indicator, i.e. Z_i takes value of one if the FT member who died was a KFT and zero otherwise. In this case, δ and β can be interpreted as the effect of death of a non-KFT and KFT, respectively. Hereafter, for ease of exposition, we only report the estimation results for the coefficients of interest, δ and β. Table 3 presents the results of the KFT heterogeneous treatment specification. Interestingly, the effects of losing a non-KFT are still negative and statistically significant. The impact of the loss of a non-KFT on ihs employment is -0.08, on ihs revenue is -0.16 and on $ihs(Rev) - ihs(Emp)$ is -0.09.[27] These findings imply that our main results are not simply driven by deaths of business owners or other top personnel and that non-KFT members also play a role in firm growth and survival.

We also find adverse effects of losing a FT member are significantly larger if the FT member is a KFT. For example, the magnitude of adverse impact of the loss of a KFT on ihs revenue is about 0.28 larger and for $ihs(Rev) - ihs(Emp)$ it is about 0.23 larger. These magnitudes imply the impact of losing a FT member who is a KFT is almost three times as large.

To analyze the heterogeneous effect with respect to human capital, we construct a relative human capital measure $Z_i = \frac{1}{N_i}(hc_i - HC_i)$ where N_i is the number of FT members that are at the firm in the quarter prior to the death shock, HC_i is the average human capital of those FT members, and hc_i is the human capital of the individual that experienced premature death. Because hc_i and HC_i are measured in logs (recall these measures are derived from prior earnings), Z_i measures the log difference in the average human capital of the remaining founding team due to the loss of a member by death.[28] If $hc_i < HC_i$, loss of the member

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[27]Because this is an estimate that averages the effect over five years, one can infer from the magnitude of these coefficient that the adverse impact of a loss of a non-KFT is not transitory.

[28]This relative measure is identical 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

will increase the average human capital of the remaining founding team, and if $hc_i > HC_i$ it will be the opposite.

Table 4 presents interaction effects with the relative human capital variable. For relative human capital, the loss of a founding team member with the mean earnings among the founding team (the main effects reported in Table 4) yields large and statistically significant reductions in employment, revenue and productivity. For example, the impact on $ihs(Rev)$ is about -0.30 and the impact on $ihs(Rev) - ihs(Emp)$ is about -0.19. These effects are about the same as the average treatment effects reported in Table 2. These results provide further evidence that our main results are not driven simply by founders and top personnel. Having said this, the loss of a FT member with a higher relative human capital yields a notably larger adverse effect of outcomes. The loss of a FT member with 25 log point higher human capital, yields a reduction in $ihs(Rev)$ that is about 0.18 larger (total effect of -0.48) and a reduction in $ihs(Rev) - ihs(Emp)$ that is 0.12 larger (for a total effect of about -0.31).

Comparing the impact of the loss of a non-KFT and a mean relative human capital yields further insights. The quantitative impact of the latter is about twice as the former. This suggests that not all non-KFT have the same impact. At the low end of human capital the impact is substantially smaller.[29] Putting the pieces together, our results point to more than just the founders (and other KFT) being important but the relative importance is closely related to the human capital that the FT member brings to the team.

We also consider heterogeneous treatment effects by the characteristics of firms. First, we consider whether the effect varies with the size of the founding team. For this purpose, we use the size of the founding team just prior to the death shock and a cutoff of 5 as small founding teams. The median size of the founding team just prior to death is around 6 (and a mean of about 13) so this threshold splits the sample into roughly equal sized groups based

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driven by entrants, stayers, and exiters. A FT member death can be considered as a form of exit that causes the change in average human capital of the remaining pool.

[29]The results in Table 4 also imply that in principle a FT member with sufficiently low relative human capital would actually boost scale and productivity. Given the magnitudes of the coefficients, this would typically require a FT member with very low relative human capital (e.g., for $ihs(Rev)$ it would require the FT member have relative human capital that is more than 40 log points lower than the mean).

on FT size just prior to the death shock. Table 5 presents the results. We find that a death shock has a larger adverse impact on scale and productivity for small ($<= 5$) compared to large founding teams. Still even for large founding teams we find negative and statistically significant effects on scale and productivity. An exception is log(productivity) where we condition on survival. Even for $ihs(Rev) - ihs(Emp)$ the impact of the loss of a FT member is relatively small for large founding teams. In contrast, for small FT the impact on all outcomes is very large. In interpreting these results, it is important to realize that this is variation in the impact of losing a FT member based on the size of the FT and not the size of the firm. The median size of the firm at the time of death is about 7 with a mean size of about 15.

Next we investigate whether the impact of losing a founding team member differs by sector. As noted previously we focus on two informative extremes: High Tech and small business-intensive industries. To identify High Tech industries we use the updated STEM classification in Goldschlag and Miranda (2016), which uses STEM employment shares following Hecker (2005).[30] We also classify industries into the top 40 small-business intensive industries using the Hurst and Pugsley (2011) methodology.

The High Tech vs. non-High Tech results are reported in Table 6. We find little evidence that the results are different between these sectors. Given a relatively small sample size, an open question might be whether this finding that High Tech does not look different is due to sample size issues. Table 7 shows that for an analysis focusing only on High Tech industries, there remains a substantial adverse impact on scale and productivity of magnitudes comparable to the main effects without interactions reported in Table 2 and the non-High Tech estimates reported in Table 6. For example, the loss of a FT member for a firm within the High Tech industry yields an impact on $ihs(Rev)$ of -0.42 (compared to the -0.35 impact in Table 2) and an impact on $ihs(Rev) - ihs(Emp)$ of -0.22 (compared to the -0.22 impact in Table 2).

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[30]This classification has recently been used to study the dynamics of High Tech industries in Decker, Haltiwanger, Jarmin, and Miranda (2018) and Goldschlag and Miranda (2016)

We find similar patterns in the Hurst and Pugsley (2011) industries (i.e., small business intensive) industries vs. other industries. In Table 8, as with the High Tech sector, we find only weak evidence of differential effects in Hurst and Pugsley (2011) industries. For the non small business intensive sectors, we continue to find large, negative, and persistent effects from the loss of a FT member. When we restrict our sample to only small business intensive industries (Table 9), we again find large adverse impacts on scale and productivity from the loss of a FT member. Therefore, our main results are not especially driven by deaths occurring in small family-owned businesses or those of plumbers, or skilled-craftsmen, whose business profits are mostly tied to their human capital.

Overall, our evidence suggests that exogenous loss of a founding team member has an adverse effects especially for key founding team members, high relative human capital team members, and for small founding teams. We find little evidence that the adverse effects are especially large or small for High Tech or for small business intensive industries. Returning to the jockey vs. the horse hypotheses regarding the determinants of successful young businesses, our findings support an important role for the jockey broadly defined as the founding team. The finding that there is an adverse impact for non-KFT and similarly for an average relative human capital team members suggests that our findings are not only driven by founders and other top personnel.

5   Concluding Remarks

In this paper we investigate the relationship between the founding teams of startups and post-entry outcomes including scale, growth, productivity, and survival. By combining employee-employer data with administrative tax information on business starts and post-entry outcomes, we provide new stylized facts about the relationship between founding team human capital and startup outcomes. We document rich attrition dynamics and assortative matching between key and non-key founding team members. Not only are these patterns

subject to the endogenous nature of these dynamics, we hypothesize that founding teams may be important for the success of startups beyond the human capital each of them brings to the founding team. Firm success may depend in important ways on the organization capital developed by the founding team in the early stages of firm formation. Organizational capital may include factors such as customer and supplier relationships, the organizational structure and processes of the business, and the business model. We think a fundamental question in understanding founding teams and young firm dynamics is whether that organizational capital is embodied in founding team and if so, whether it is important only among key founding members. The latter, of course, is likely related to the ex ante human capital of founding team members so there is likely to be some interaction of the impact of human capital and organizational capital embodied in founding team members.

We use the premature death of founding team members in a difference-in-difference framework to identify the causal impact of losing a founding team member. A matching strategy is used to create a control group of firms that are observably similar to our death shocked (treated) firms. Our estimates imply that exogenously separating a founding team member from a startup has a negative, significant, and persistent impact on scale, both employment and revenue, and labor productivity. Losing a founding team member also reduces the probability of survival. We present evidence that while this extensive margin is important, an important fraction of the adverse impact of losing a founding team member is on the intensive margin.

We also investigate how the impact varies with founding team characteristics and firm characteristics. We find that the impact of losing a founding team member due to premature death is especially large for key founding team members, high human capital founding team members, and for small founding teams. Statistically significant adverse effects are still present for founding team members that are not founders (or other top personnel) or have average relative human capital within the firm. Moreover, the effects of losing a non-key founding team member or mean relative human capital member of the founding team are

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quantitatively large, highlighting the importance of taking a broader view of the founding team. We also find that our results are not being driven by the High Tech industries nor alternatively by the small business intensive industries.

We interpret our findings as being consistent with the hypothesis that the founding team (inclusive of but also beyond the founders themselves) is important in accounting for post-entry dynamics of firms. One concern about this interpretation is whether our results are being driven by the impact of losing a worker whether or not they are members of the founding team. The evidence in Jager and Heining (2019) argues against this view. They find that small businesses that lose a worker due to premature death suffer only a relatively small, temporary reduction in employment while we find a large, persistent impact. It still may be that younger firms are more vulnerable to adverse events – a hypothesis that deserves further investigation.[31]. An additional question of interest is the extent to which our results are driven by the disruption effect of losing a founding team member via premature death. There is arguably an emotional distress adverse impact on team capital from a death for small founding teams who have been working together closely. We think two aspects of our findings suggest to us that this is not a primary factor in accounting for our results. First, we find that the adverse impact is very persistent with the adverse impact in year 5 after death about the same magnitude as year 2. Second, if this is the primary factor then the emotional distress would have to be more severe for higher human capital and key founding team members. [32]

Taken together, our results demonstrate the critical role of founding teams in shaping the growth dynamics and survival of young firms. Consistent with the large and persistent

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[31]In future drafts, we plan to examine the impact of a premature death of a founding team member for firms between 6-11 years of age.

[32]Relatedly, Jaravel, Petkova, and Bell (2018) provide evidence against this mechanism of emotional distress among surviving co-inventors by turning to the fact that the treatment effect is long-lasting and also larger when losing a high-achieving collaborator. It is also worth noting that SYZZ find that the retirement of founders yields about the same adverse impact as a premature death of a founder. Retirements are a less plausibly exogenous separation but it is instructive that the effects of retirements are similar to those for premature deaths in their setting. It would be interesting to explore alternative forms of exogenous separations in future work.

adverse impact of losing a founding team member, organizational capital formed during the early stages of a firms life-cycle appears to be embodied in the founding teams. Though it raises many questions for future research, this study sheds light on founding teams as a central piece to understanding the sources of the enormous variation in startup performance.
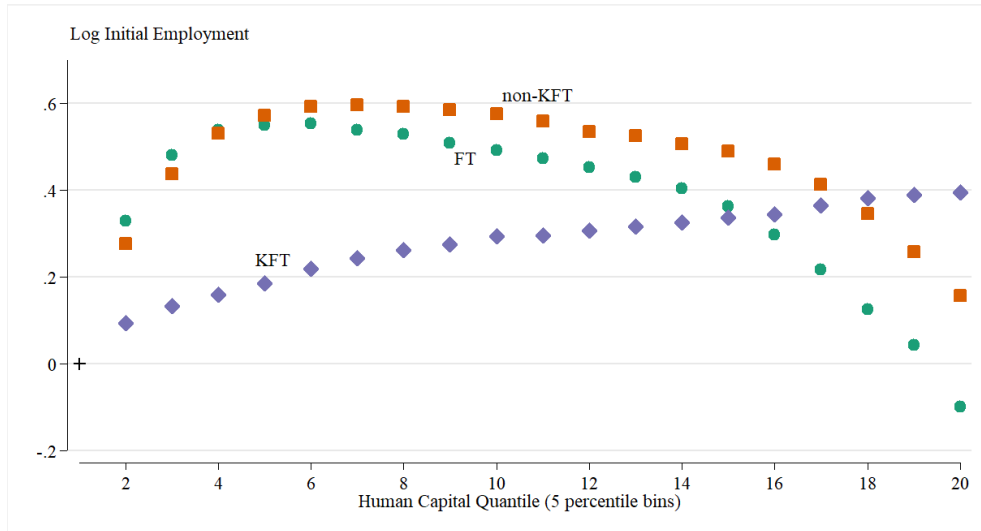
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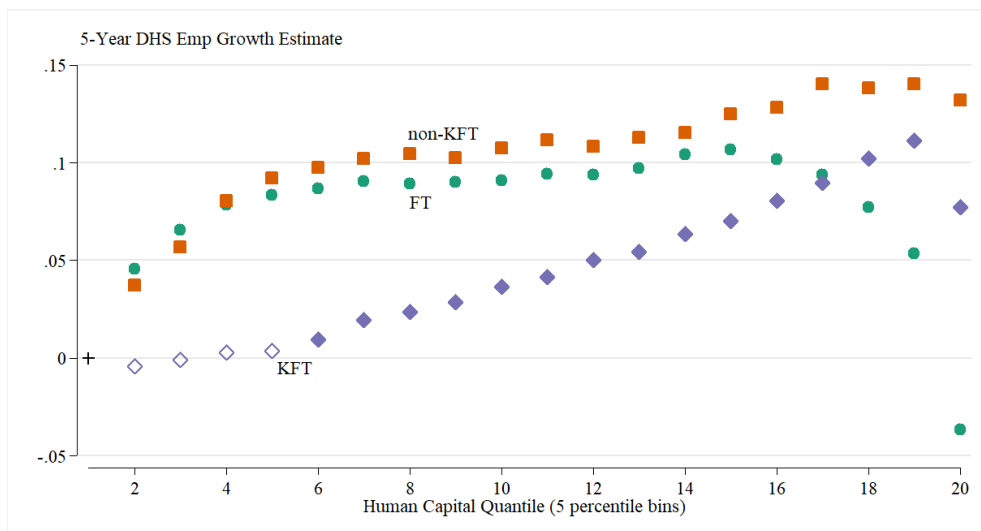
Figures

Figure 1: Human Capital and Log Initial Employment

Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for initial size and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group bin 1.
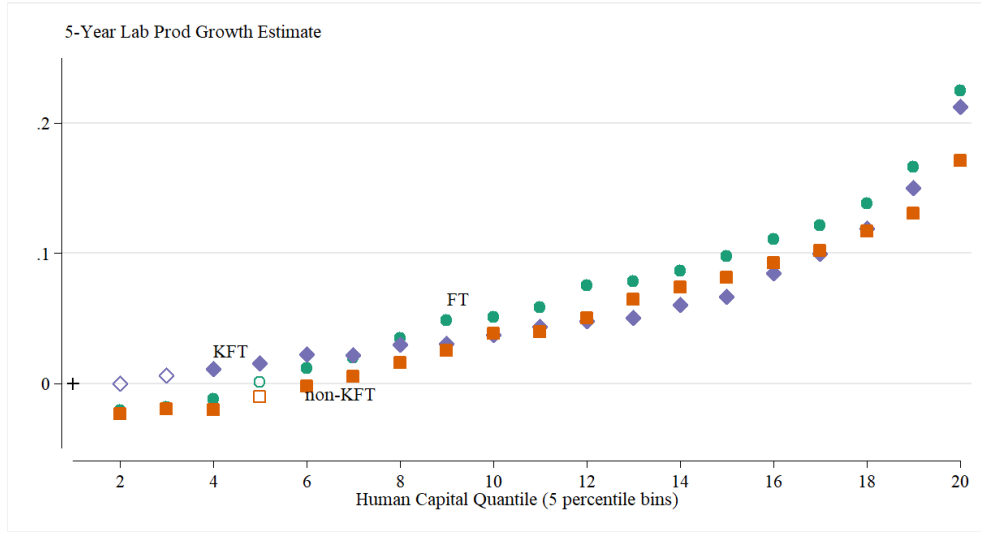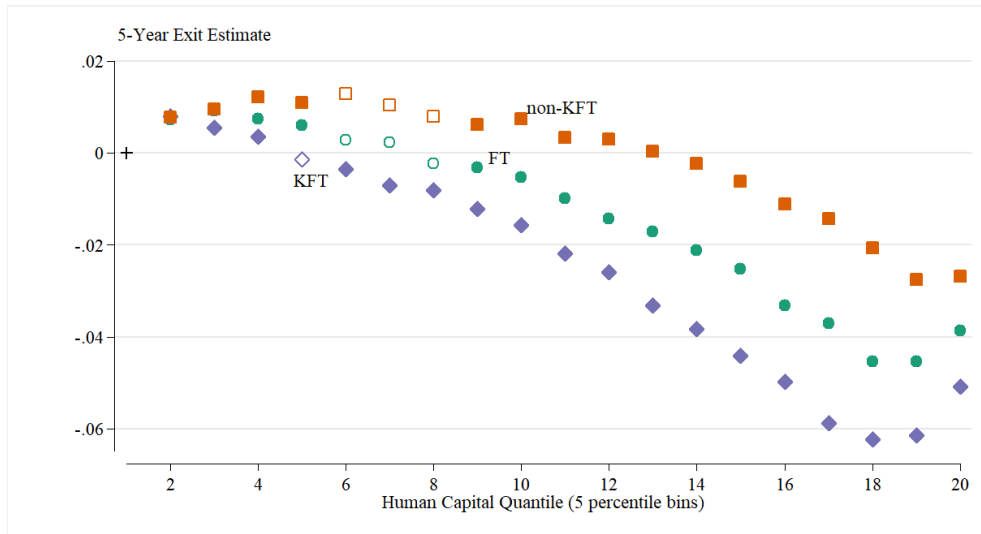
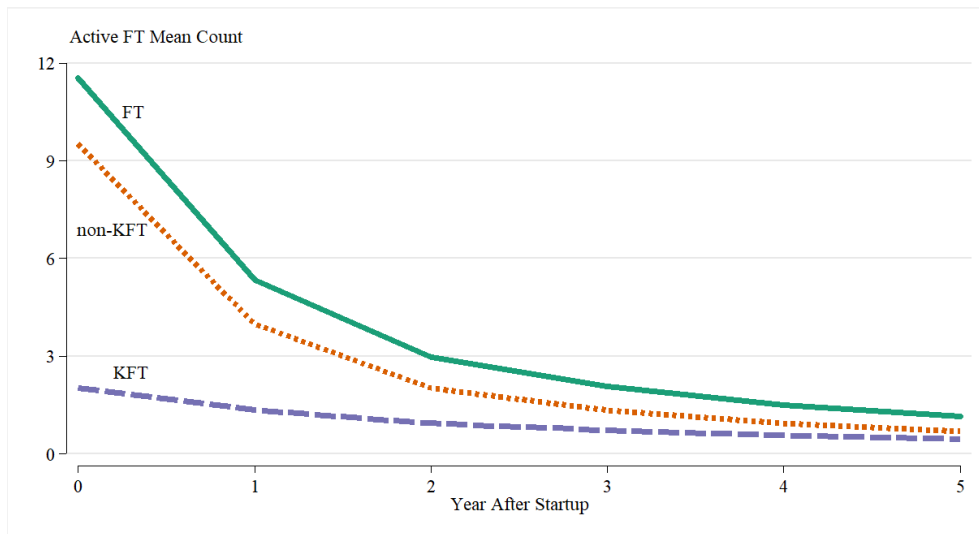Figure 2: Human Capital and 5-Year Employment Growth

Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for initial size and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group bin 1.

Figure 3: Human Capital and 5-Year Productivity Growth

Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for initial productivity and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group bin 1.

Figure 4: Human Capital and Exit

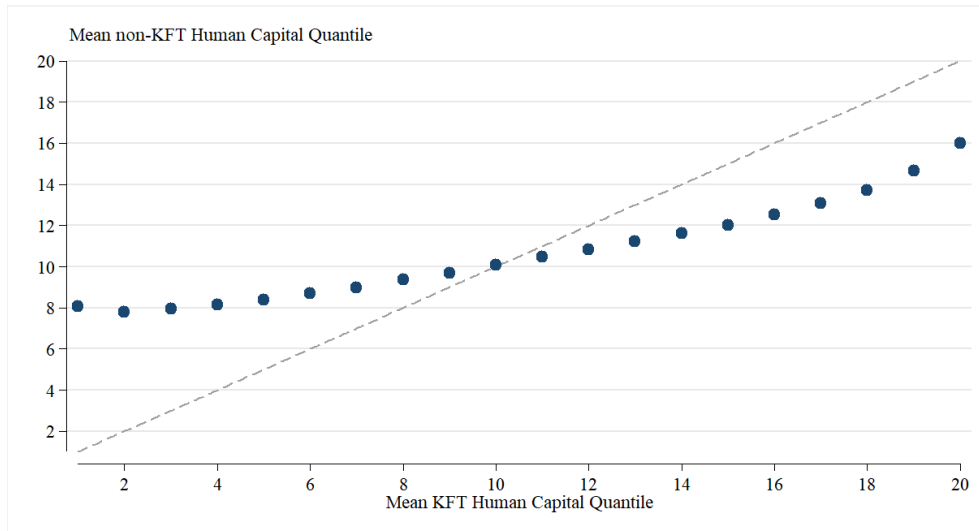Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Controlling for initial size and industry-year effects. Hollow points $\rightarrow p > 0.05$. Reference group bin 1.
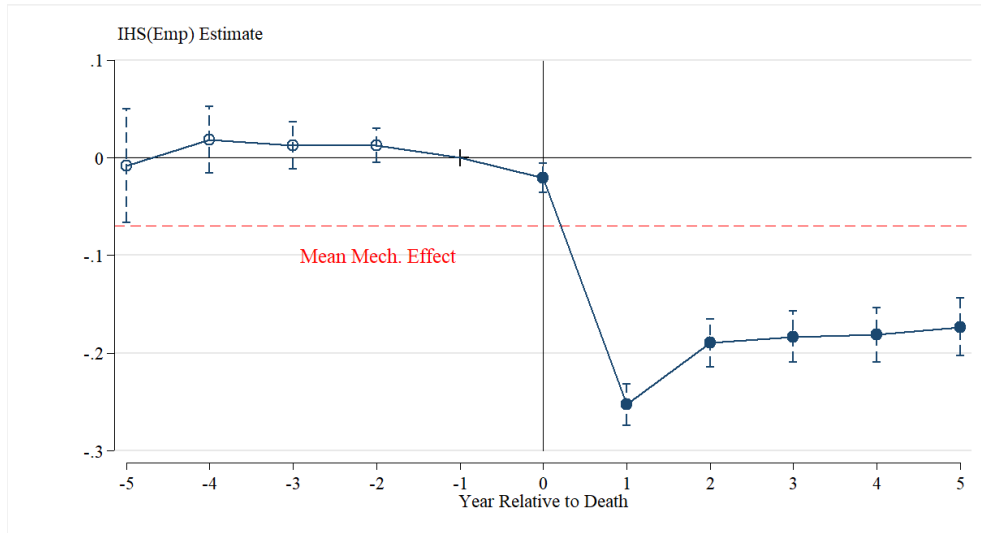
Figure 5: Founding Team Attrition

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

Figure 6: Human Capital Composition of KFT and non-KFT

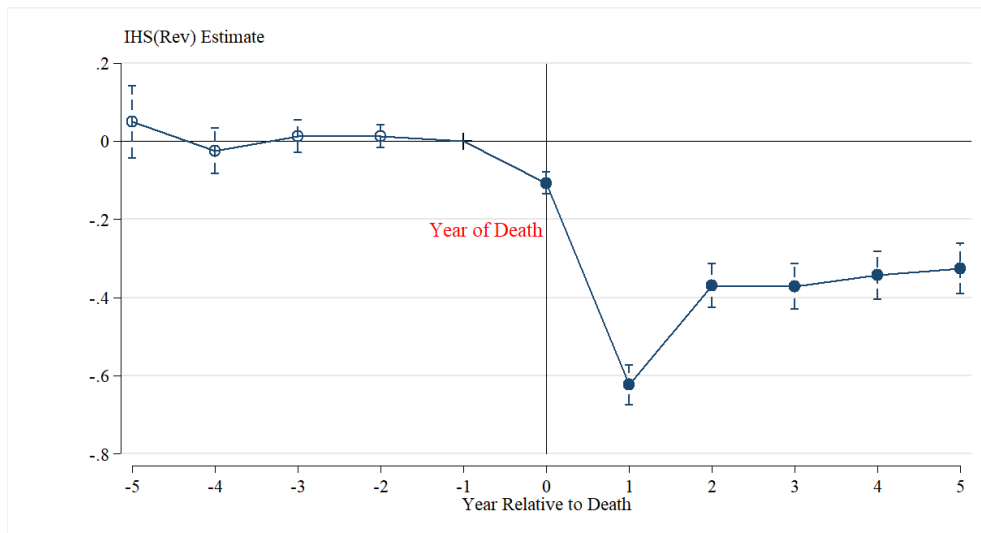Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes:

Figure 7: Founding Teams Death Shocks and $ihs(Emp)$

Source: Founding 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 $t-1$.
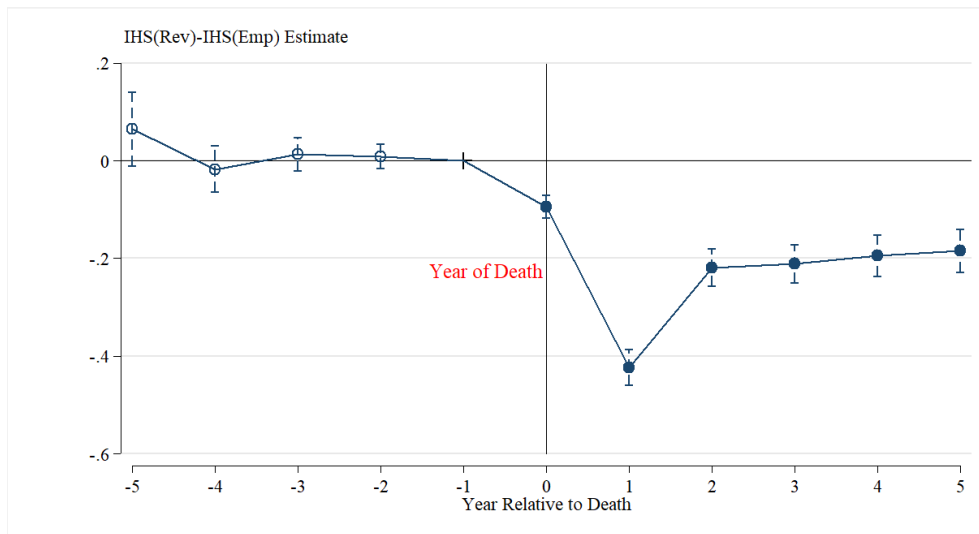
Figure 8: Founding Teams Death Shocks and $ihs(Rev)$

Source: Founding 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 $t-1$.
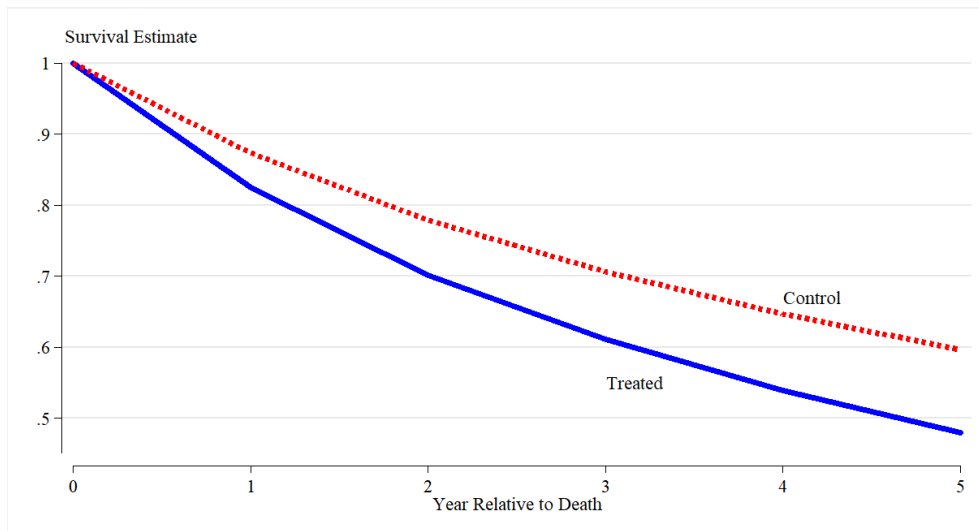
Figure 9: Founding Teams Death Shocks and $ihs(Rev) - ihs(Emp)$

Source: Founding 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 $t - 1$.
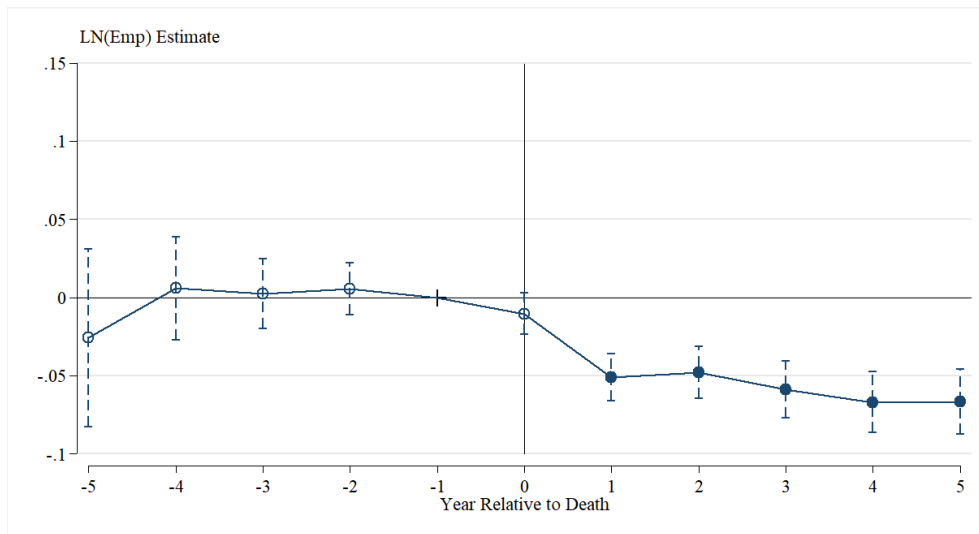
Figure 10: Founding Teams Death Shocks and Survival

Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Cox estimate 0.35 (0.013).

Figure 11: Founding Team Death Shocks and log(Emp)

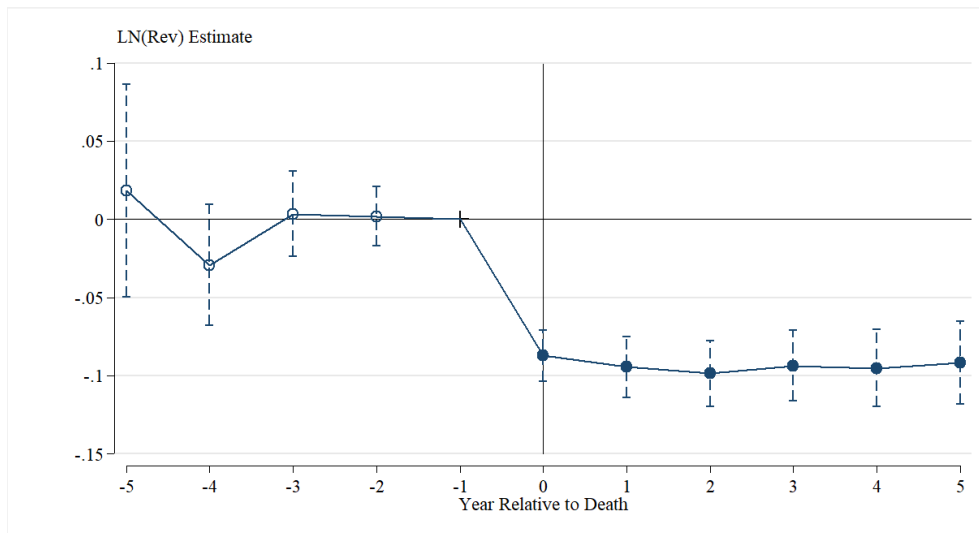Figure 12: Founding Team Death Shocks and log(Rev)

Figure 13: Founding Team Death Shocks and log($Prod$)

Source: Founding 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 $t - 1$.
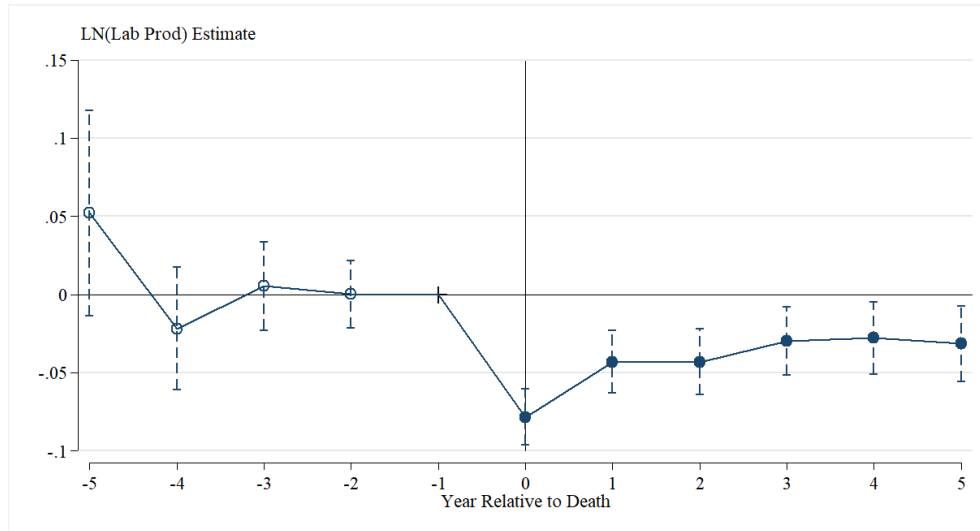
Tables

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

	Treated	Controls	nobs
Firm Age	1.367	1.369	52000
Log(Employment)	1.992	1.955	52000
Log(Revenue)	6.421	6.458	35000
Log(Productivity)	4.336	4.474	35000
Avg Age of FT	36.22	36.29	52000

Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Means of key variables for the treated (death shock cases) and controls in the death shock year.
Observation counts rounded to avoid the disclosure of sensitive information.

Table 2: Pre Post Main Effects

	(1) $ihs(Emp)$	(2) $ihs(Rev)$	(3) $ihs(Rev)- ihs(Emp)$	(4) $\log(Emp)$	(5) $\log(Rev)$	(6) $\log(Prod)$
$Post$	.2521***	.3514***	.1543***	.07102***	.02709***	-.03798***
	(.006611)	(.01343)	(.009445)	(.005151)	(.006346)	(.00611)
$Post*Treated$	-.1588***	-.347***	-.2223***	-.04799***	-.09425***	-.0475***
	(.008514)	(.01874)	(.01335)	(.00698)	(.009074)	(.008213)
Observations	306,000	213,000	213,000	280,000	200,000	200,000
R^2	.7156	.6024	.6029	.8765	.8933	.8185
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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 3: KFT Heterogeneous Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	$ihs(Emp)$	$ihs(Rev)$	$ihs(Rev)-$ $ihs(Emp)$	$\log(Emp)$	$\log(Rev)$	$\log(Prod)$
$Post*Treated$	-.07929***	-.1603***	-.08689***	-.02338**	-.04861***	-.02023*
	(.01217)	(.02369)	(.01628)	(.009695)	(.01203)	(.01074)
$Post*KFT*Treated$	-.1727***	-.4381***	-.3183***	-.05595***	-.1103***	-.06543***
	(.01692)	(.03808)	(.02734)	(.01393)	(.01835)	(.01669)
Observations	306,000	213,000	213,000	280,000	200,000	200,000
R^2	.7158	.6033	.6039	.8766	.8934	.8185
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Regressions specifications also include $Post$ and $Post*KFT$, the estimates for which are excluded for simplicity.

Table 4: Human Capital Heterogeneous Effects

	(1) $ihs(Emp)$	(2) $ihs(Rev)$	(3) $ihs(Rev)-$ $ihs(Emp)$	(4) $\log(Emp)$	(5) $\log(Rev)$	(6) $\log(Prod)$
$Post*Treated$	-.1384***	-.2918***	-.185***	-.04079***	-.0781***	-.03843***
	(.009763)	(.02068)	(.01467)	(.007942)	(.0102)	(.009195)
$Post*HC*Treated$	-.2794***	-.7081***	-.4613***	-.08633**	-.2216***	-.1379***
	(.05153)	(.1241)	(.08722)	(.04402)	(.05999)	(.05293)
Observations	234,000	167,000	167,000	215,000	157,000	157,000
R^2	.7146	.6036	.6087	.8775	.8916	.8197
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Regressions specifications also include $Post$ and $Post*HC$, the estimates for which are excluded for simplicity. HC is the firm-level change in average founding team human capital (prior earnings) due to the death shock (treatment), $\frac{1}{N_{t-1}}(hc_i - HC_{t-1})$ where N_{t-1} is the number of active founding team members in the quarter prior to death, hc_i is the human capital of the individual that experienced premature death, and HC_{t-1} is the average human capital of active founding team members in the quarter prior to death.

Table 5: Firm Size Heterogeneous Effects (Small $\leq$ 5)

	(1) $ihs(Emp)$	(2) $ihs(Rev)$	(3) $ihs(Rev)-$ $ihs(Emp)$	(4) $\log(Emp)$	(5) $\log(Rev)$	(6) $\log(Prod)$
$Post*Treated$	-.06795***	-.08958***	-.02788	-.02982***	-.04409***	-.009804
	(.01505)	(.02692)	(.01751)	(.0113)	(.01343)	(.01196)
$Post*Small*Treated$	-.145***	-.4341***	-.3295***	-.03007**	-.08606***	-.06517***
	(.01818)	(.03693)	(.02558)	(.01438)	(.01815)	(.01638)
Observations	306,000	213,000	213,000	280,000	200,000	200,000
R^2	.7157	.6033	.6042	.8765	.8934	.8185
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Regressions specifications also include $Post$ and $Post*Small$, 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: High Tech Heterogeneous Effects

	(1) ihs(Emp)	(2) ihs(Rev)	(3) ihs(Rev)− ihs(Emp)	(4) log(Emp)	(5) log(Rev)	(6) log(Prod)
*Post * Treated*	-.1578***	-.3444***	-.222***	-.04645***	-.09443***	-.04925***
	(.008589)	(.01892)	(.01349)	(.007001)	(.009098)	(.008311)
*Post * HT * Treated*	-.0292	-.07328	-.007757	-.04401	.004768	.04733
	(.04506)	(.09648)	(.06872)	(.03949)	(.05257)	(.04198)
Observations	306,000	213,000	213,000	280,000	200,000	200,000
R^2	.7156	.6024	.6029	.8765	.8933	.8185
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Regressions specifications also include *Post* and *Post * 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 7: High Tech Main Effects

	(1) $ihs(Emp)$	(2) $ihs(Rev)$	(3) $ihs(Rev)-$ $ihs(Emp)$	(4) $\log(Emp)$	(5) $\log(Rev)$	(6) $\log(Prod)$
$Post$	.254***	.284***	.09163	.1054***	-.01095	-.08342**
	(.04159)	(.07953)	(.05601)	(.03392)	(.04509)	(.0378)
$Post*Treated$	-.2043***	-.4194***	-.2197***	-.09226*	-.09673	-.0006171
	(.05373)	(.1143)	(.08014)	(.04741)	(.06292)	(.0475)
Observations	9,200	6,800	6,800	8,400	6,400	6,400
R^2	.7165	.6041	.5293	.856	.866	.7229
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Includes only firms in High Tech industries.

Table 8: Hurst & Pugsley Heterogeneous Effects

	(1) ihs(Emp)	(2) ihs(Rev)	(3) ihs(Rev)− ihs(Emp)	(4) log(Emp)	(5) log(Rev)	(6) log(Prod)
$Post*Treated$	-.1531***	-.323***	-.2021***	-.04895***	-.09212***	-.04543***
	(.01064)	(.02275)	(.01593)	(.008564)	(.01103)	(.00979)
$Post*HP*Treated$	-.0184	-.07884*	-.06571**	.002983	-.00725	-.006766
	(.01753)	(.04012)	(.02919)	(.01473)	(.01937)	(.01797)
Observations	306,000	213,000	213,000	280,000	200,000	200,000
R^2	.7156	.6025	.603	.8765	.8933	.8185
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Regressions specifications also include $Post$ and $Post*HP$, the estimates for which are excluded for simplicity. HP is equal to 1 if the firm is in a Hurst and Pugsley (2011) industry and zero otherwise.

Table 9: Hurst & Pugsley Main Effects

	(1) ihs(Emp)	(2) ihs(Rev)	(3) ihs(Rev)− ihs(Emp)	(4) log(Emp)	(5) log(Rev)	(6) log(Prod)
Post	.2148***	.3086***	.1397***	.06358***	.01828	-.04082***
	(.0108)	(.02341)	(.01718)	(.008919)	(.0113)	(.01123)
Post * Treated	-.172***	-.4023***	-.2684***	-.04531***	-.09912***	-.05264***
	(.0139)	(.03294)	(.0244)	(.01194)	(.01587)	(.01502)
Observations	92,500	63,500	63,500	84,000	59,500	59,500
R^2	.6925	.5771	.5611	.8448	.8759	.7804
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y	Y	Y

Source: Founding 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. Includes only firms in Hurst and Pugsley (2011) industries.

A Appendix

For the specification in the main text, the first order conditions for founding team and non-founding team employment if the firm produces are given by:

$$M_{i1}(1 - \chi_{i1})^{\kappa}\theta(L_{i1}^{FT} + \gamma L_{i1}^{NT} - f)^{\theta-1} - w_1 - \lambda = 0 \tag{11}$$

$$M_{i1}(1 - \chi_{i1})^{\kappa}\theta\gamma(L_{i1}^{FT} + \gamma L_{i1}^{NT} - f)^{\theta-1} - w_1 = 0 \tag{12}$$

where λ is the multiplier for the constraint $L_{i1}^{FT} \leq (1 - \chi_{i1})N$. It is apparent that for $\gamma < 1$, $L_{i1}^{NT} > 0$ only if $\lambda > 0$. This implies we can simplify these first order conditions for the ranges where only founding team are employed and when non-founding team members are employed. The optimal employment, revenue and revenue productivity are presented in the main text.

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

$$L_{i1}^{FT} = (M_{i1}(1 - \chi_{i1})^{\kappa}\theta/w_1)^{1/(1-\theta)} + f \tag{13}$$

Revenues are given by:

$$R_{i1} = (M_{i1}(1 - \chi_{i1})^{\kappa}(M_{i1}(1 - \chi_{i1})^{\kappa}\theta/w_1)^{\theta/(1-\theta)} \tag{14}$$

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

$$R_{i1}/L_{i1}^{FT} = (w_1/\theta)(1 - f/L_{i1}^{FT}) \tag{15}$$

This implies that as M_{i1} declines or χ_{i1} increases that productivity declines. In addition, profits are given by:

$$\pi_{i1} = L_{i1}^{FT}(w_1(1/\theta - 1)) - fw_1/\theta \tag{16}$$

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.

In this appendix, we also consider some modifications of the model in the main text. Suppose that the founding team is still of size N with ω the fraction of the founding team that is high skilled and $1 - \omega$ the fraction low skilled. To make things simple, the knowledge capital is embedded only in the skilled so the productivity in period 1 is given by $M_{i1}(1 - \chi_{i1})^{\kappa}$ but where χ_{i1} is now the fraction of the skilled workers who are subject to exogenous attrition. The fixed cost of the formation period is now $\omega w_{0,S} + (1 - \omega)w_{0,NS}$ where w_{0S} is the wage of the skilled etc. Revenue is given by:

$$R_{i1} = M_{i1}(1 - \chi_{i1})^{\kappa}((L_{i1,S}^{FT} + \gamma_S L_{i1,S}^{NT})^{\nu}(L_{i1,NS}^{FT} + \gamma_{NS}L_{i1,NS}^{NT})^{1-\nu} - f)^{\theta} \tag{17}$$

In this formulation, both skilled and unskilled founding team members are preferred to non-founding team members but this permits the possibility that for example $\gamma_S < \gamma_{NS} = 1$.

That is, there is nothing special about the founding team unskilled. They might be necessary as an input during the formation period but they are perfect substitutes with non-founding team members thereafter. One could enrich this further by embedding some knowledge in unskilled founding team members but then assuming (or testing) $\kappa_S > \kappa_{NS}$. The formulation above implicitly assumes $\kappa_{NS} = 0$.

A.1 Additional Figures and Tables

Table A1: Labor Productivity, Survival, and Growth

	(1) Firm Exit	(2) Emp Growth
$\log(LabProd_{t-1})$	-0.0640***	0.2255***
	(0.00009)	(0.0002)
Observations	22,200,000	22,200,000
R^2	0.0537	0.1021
Industry-Year FE	Y	Y

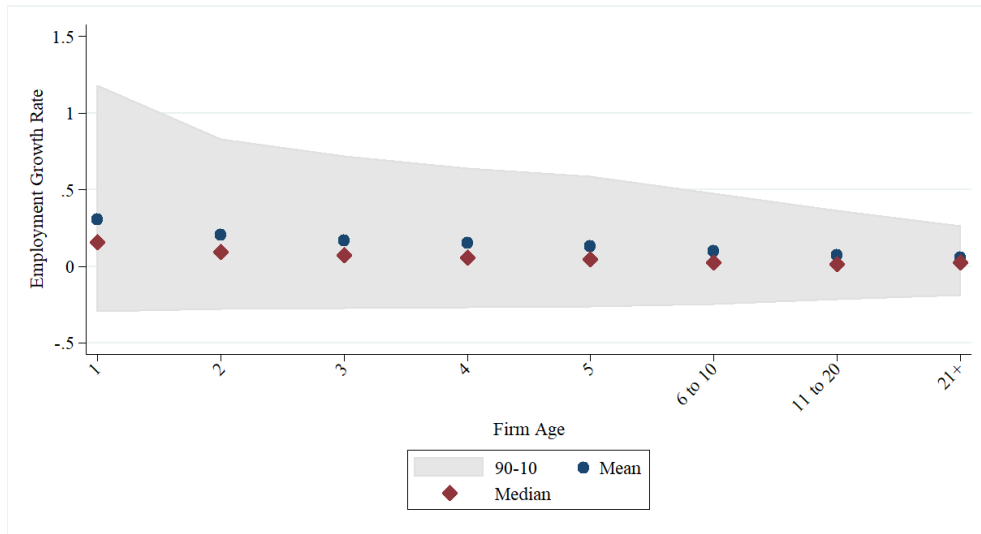Source: Founding Team Database (LBD, LEHD), author's calculations.
Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Observation counts rounded to avoid the disclosure of sensitive information.
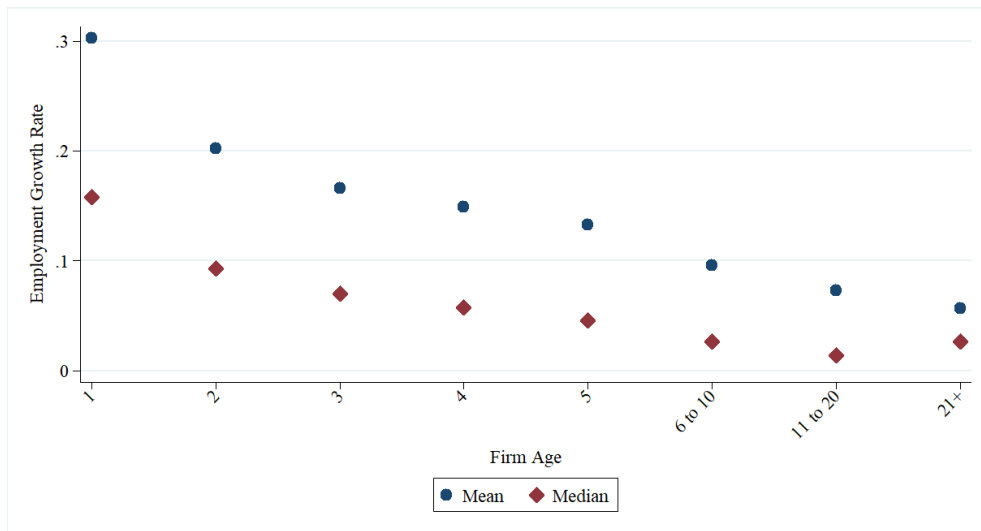
Figure A1: Firm Exit Rates and Firm Age
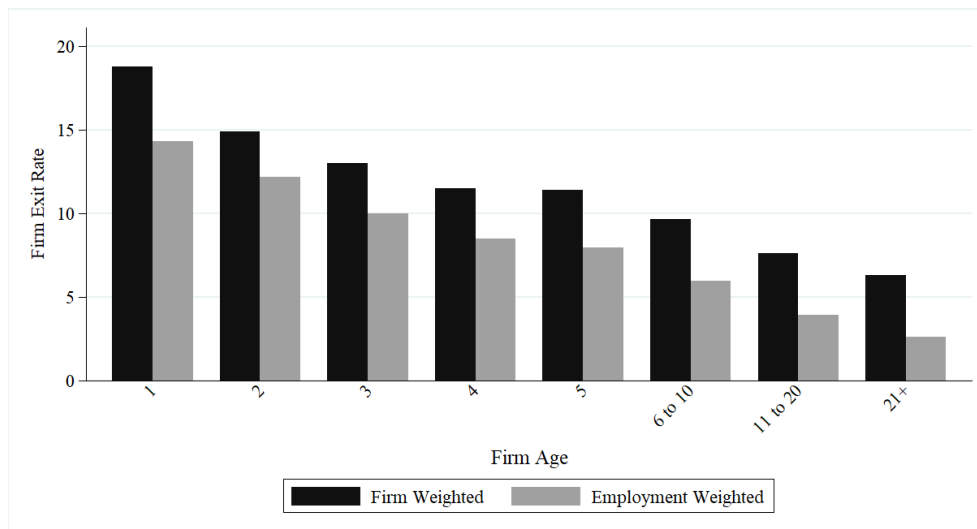
Source: Founding Team Database (LBD, LEHD), author's calculations.

Figure A2: Firm Age and Employment Growth

Figure A3: Firm Age and Mean and Median Employment Growth