Too Much Talent? The Tradeoff Between Human and Non-Human Assets in Technology Startups

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Abstract

While human capital is a key resource for startup firms, hiring the best talent involves a tradeoff: allocating resources to human assets necessarily detracts those away from non-human assets. Striking the right balance between the two inputs is especially challenging under demand uncertainty. We formalize this tradeoff using a theoretical approach, which predicts that higher uncertainty increases the likelihood that firms inefficiently devote too much or too little to human assets, undermining firm performance. We find empirical support for these ideas using administrative survey data from the US Census Bureau. Furthermore, we decompose labor spending into quantity (number of employees) and quality (average wages) and find that more quality does not necessarily reduce inefficiency. Labor quantity, specifically under-hiring, is associated more significantly with inefficiency.

Keywords: Resource allocation; Human capital; Entrepreneurship; Technology startups; Firm performance; Stochastic frontier analysis.

1 Introduction

Human capital is a key resource for entrepreneurial firms (Dierickx and Cool 1989, Coff 1997, Campbell et al. 2012, Sakakibara and Balasubramanian 2020). Beyond the founding team, early employees are important building blocks of a nascent organization as these individuals bring valuable knowledge and experiences from prior employment (Agarwal et al. 2016, Brymer and Rocha 2021). In addition to their immediate contribution to the nascent organizations, early employees leave a lasting effect as they tend to imprint the organization with specific routines and role boundaries (Beckman et al. 2007, Sorenson et al. 2021). Given the significance of talent in this context, much attention has been paid to the challenges and ways startups can effectively recruit top-tier talent (Wasserman 2012, Honore and Ganco 2020, Choi et al. 2023).

However, hiring the best talent involves a key tradeoff: given resource constraints, allocating resources to developing human assets detracts those away from investing in non-human assets such as equipment, computing servers, or buildings. Investing in human assets has largely been explored in isolation, but they are part of a broader set of resources that must be allocated (e.g., Maritan and Lee 2017, Belenzon et al. 2019). As such, resource allocation is among the chief concerns of entrepreneurs (Ansoff 1965, Chandler 1962, p. 11, Rumelt et al. 1991) because of the challenges of allocating resources efficiently under great demand uncertainty (Knight 1921, Wu and Knott 2006, Hietaniemi et al. 2024). Technology startups are particularly vulnerable to the consequences of demand uncertainty because they typically enter new markets with unproven technologies and lack a track record of prior resource allocation decisions to draw upon.

This paper studies how uncertainty determines the resource allocation between human assets ("labor") and non-human assets and its performance implications. Following prior research that examines strategic decisions using formal modeling (e.g., Hannah et al. 2021, Makadok et al. 2018), we consider a decision maker (the entrepreneur) who allocates the firm's budget between labor and non-labor inputs to create a product that faces uncertain demand. We assume that allocation decisions determine the product's development level. This is to capture the fact that some technology startups introduce highly developed products and others simpler ones.[1] For example, to compete in the cash register market that was dominated by the incumbent National Cash Register, startups entered the market in the 1960's by developing a more sophisticated cash register using electronic components to compete on quality (Rosenbloom and Christensen 1994: 669-670).[2] However, startups also often aim for a less developed or simpler product. Consider the case of the photocopier industry. While Xerox dominated the market with its large, complex, and fast photocopiers, Canon entered by developing a more limited photocopier that was small enough to reach a niche market inadequately serviced by the incumbent (e.g., Jacobson and Hillkirk 1986).[3] Nevertheless, whether the startup pursues a highly developed versus a simpler product, a shared challenge is the uncertainty regarding how much demand the product will generate. Therefore, the entrepreneur's task is to predict the likely demand at the chosen level of product development and allocate resources accordingly to match that demand.

We focus on how demand uncertainty determines the budget allocation to human and non-human inputs leading to a given product development level and, subsequently, performance. Our first theoretical result is that increased demand uncertainty increases the share of the budget devoted to human assets. This is because increased uncertainty means that upside demand realizations are more likely, incentivizing the firm to take a higher risk of

[1]This is in part motivated by the idea of disruptive innovation by Christensen (1997) in which some entrants intentionally begin with a lower-quality product in pursuing a niche, under-served market.

[2]Another more recent example: Startups in the electronic design automation industry often produce better quality products. They "came up with better algorithms that made their simulators significantly faster than those of [Synopsys, Cadence, and Mentor, the three largest firms in the EDA industry]" (Henkel et al. 2015: 303).

[3]This is not exclusive to information technology industries. New entrants using hydraulic technologies in earth-moving equipment in the 1940s found strong demand despite being smaller and less powerful than the dominant cable-powered machines (Christensen and Bower 1993).

developing products further, and developing products is a (human) talent-intensive task. Furthermore, we decompose investments in human assets into the quantity (i.e., number of employees) and quality (i.e., average wages) of labor. The model prescribes that neither of these factors should decrease too much with demand uncertainty. Moreover, at least one should increase with uncertainty because investment in human assets is, by definition, average wages times quantity.

The model also describes how demand uncertainty affects a firm's outcomes. Because of uncertainty, a direct implication is that entrepreneurs are likely to make inefficient decisions in resource allocation, which translates into an inverted U-shape relationship between the share of resources allocated to human assets ("labor share") and startup performance. Too little or too much allocation to labor results in reduced performance because of the tradeoff between labor and non-labor inputs. In addition, increased demand uncertainty entails increased inefficiency, which may or may not be ameliorated by more quality or quantity of workers.

We empirically study these ideas using data from the Annual Survey of Entrepreneurs, a representative survey of U.S.-based startups administratively conducted by the U.S. Census Bureau (Foster and Norman 2016). To focus on technology entrepreneurship rather than small businesses, we condition on 6,100 startups that invest in research and development (R&D). A key advantage of the ASE is the ability to distinguish each startup's R&D spending on labor versus non-labor (e.g., equipment, software).[4] We begin by describing the nature of R&D resource allocation for startups. The average startup allocates 41% of its R&D spending to labor, but we find significant variation both within and across industries. For instance, the average labor share in R&D spending in the real estate sector is 17%, while that in the information sector is 62%.

[4]Though the ASE has been conducted annually between 2014 and 2016, we use only the 2014 survey as R&D spending-related questions were not included in later vintages. For more on the ASE, see: https://www.census.gov/programs-surveys/ase.html

We then analyze the empirical relationship between demand uncertainty and R&D labor share. We find that one standard deviation increase in demand uncertainty is associated with a 5% increase in labor share, computed over a sample mean of 40%. Moreover, when increasing uncertainty, firms tend to hire more R&D workers but not necessarily alter the compensation of the workers they pursue. That is, uncertainty-driven additional investment in labor comes from quantity, not quality.

When studying R&D labor share and firm performance, we find an inverted U-shaped relationship between labor share and survival, employment growth, and revenue growth. Firm performance rises with labor share up to a point after which it falls as startups over-allocate their R&D spending to labor. We then analyze demand uncertainty, quantity, and quality of workers as potential sources of firm inefficiency using frontier analysis (e.g., Chen et al. 2015, Wu and Knott 2006). We find that demand uncertainty is unambiguously associated with greater inefficiencies in each of the performance measures. In contrast, labor quantity is significantly associated with efficiency, while labor quality is not. More specifically, startups' deviation from the no-uncertainty optimal labor share in R&D spending appears to be more driven by under-hiring of employees and less by the level of wages paid to their employees. Taken together, these results suggest that resource allocation in labor versus non-labor can characterize firm performance, and that much of the inefficiency in this allocation decision is in the quantity rather than the quality of talent ushered into the firm.

Our main contribution is identifying the role of uncertainty in resource allocation for technology startups. A large literature documents the importance of uncertainty on startup performance (e.g., Knight 1921, Wu and Knott 2006). We extend this literature by first formally describing uncertainty's role in the tradeoff between developing human assets and non-human assets of the firm and then illustrating its performance implications. Prior research has identified the importance of human assets for firm performance (e.g., Coff 1997, Unger et al. 2011, Campbell et al. 2012, Sakakibara and Balasubramanian 2020). Our contribution to this research stems from showing that human assets impact firm performance as one factor in the context of a broader resource allocation decision (Levinthal and Wu 2010). Furthermore, we contribute by decomposing labor investments into labor quality and quantity. We find that the latter is a significant contributor to inefficiencies in labor allocation decisions. This highlights a potential tradeoff in hiring the "best" versus "more" employees. Finally, our study contributes to the resource allocation literature by focusing on technology startups, which have received less attention largely due to data limitations. Contrary to multi-unit businesses that can benefit from redeploying resources (e.g., Karim and Capron 2016, Belenzon and Tsolmon 2016, Lovallo et al. 2020, Balasubramanian and Sakakibara 2023), technology startups tend to be single-unit firms. As such, they are heavily influenced by their initial resource allocation decisions, which are made under high levels of demand uncertainty and resource constraints (McMullen and Shepherd 2006), thereby elevating resource allocation under uncertainty as a central strategic concern.

2 Background

Resource allocation is a key strategic decision for firms (Rumelt et al. 1991, Ansoff 1965, Maritan and Lee 2017). Among other dimensions, different allocations of resource can shape the firm's diversification efficiency (Penrose 1959), adjustment costs for growth (Chandler 1962), and flexibility (Ansoff 1965). Despite the importance of resource allocation decisions, prior research has documented difficulties in allocating resources efficiently, stemming from cognitive biases (Bardolet et al. 2011), long-term performance concerns (Arrfelt et al. 2013), tension between new and existing capabilities (Maritan 2001), and organizational barriers (Danneels 2007, Lovallo et al. 2020).

At the heart of inefficient resource allocation decisions is uncertainty. One key dimension of uncertainty is that of demand for new products (Wu and Knott 2006). Because firms cannot know ex-ante whether consumers will like the new product they develop, their resource allocation decisions may lead to under- or over-investments in the product that will lead to mismatch with the realized demand (e.g. Holmstrom 1989, He and Tian 2013, Troyer and Ahuja 2015 for under-investment; and Ahuja and Novelli 2017 for over-investments in R&D). To mitigate the detrimental effects of uncertainty in resource allocation, an emerging stream of research on resource redeployment and reallocation suggests that flexibility can be a helpful approach (e.g., Karim and Capron 2016, Helfat and Eisenhardt 2004, Sakhartov 2017, Dickler and Folta 2020, Lovallo et al. 2020). An important finding in this literature is that multi-unit firms can redeploy employees inside the firm in response to unexpected changes in the environment (Belenzon and Tsolmon 2016, Belenzon et al. 2019). Redeployability of human assets allows multi-unit firms to hire more aggressively when facing uncertainty about future market demand.

However, these benefits from resource redeployment do not necessarily extend to standalone companies. In particular, technology startups are predominantly standalone rather than multi-unit firms (Haltiwanger 2012). Thus, startups are structurally limited—compared to multi-unit businesses—in their ability to redeploy under-utilized talent to other parts of the organization (e.g., Balasubramanian and Sakakibara 2023). As such, excessive resource allocation towards labor can be especially costly.

Technology startups face additional challenges in making resource allocation decisions. First, technology startups often operate in a new market or use nascent technologies, which entail heightened demand uncertainty when allocating resources (McMullen and Shepherd 2006, Packard et al. 2017, Moeen et al. 2020). Second, reflecting their liability of newness (Aldrich and Auster 1986, Stinchcombe 1965), startups lack an established track record of prior resource allocation decisions, in contrast to established firms that can use their prior decisions to help resolve demand uncertainty for their products (Cohen and Levinthal 1990, Balasubramanian and Lieberman 2010). As a result of high demand uncertainty, startups are prone to making inefficient resource allocation decisions, which can manifest as under- or over-hiring.

At the same time, hiring is critically important for startups. The stakes for hiring are high for startups because, with their small size, each new hire represents a relatively large addition (e.g., Ganco et al. 2019, Agarwal et al. 2016, Burton et al. 2016, Cooper et al. 1994). Several studies show that initial employees at startups make a lasting impact on their nascent employers (Burton and Beckman 2007, Choi et al. 2023, Hietaniemi et al. 2024). Consequently, given the importance of human capital for startups, much attention has been placed on how startups can successfully hire and retain talent (Wasserman 2012, Roach and Sauermann 2015, Kim 2018).

However, it is not clear how technology startups allocate resources towards human and non-human assets under uncertainty. While the focus has been on the levels of startup spending more generally ("burn rates") as a frequent reason for failure in entrepreneurship, less is known about the performance consequences of resource allocation decisions.[5] To study this issue among technology startups, we begin with a formal model as the organizing framework. We then derive and empirically test some key implications using a dataset of R&D-active startups in the US.

3 Theoretical Framework

We study how labor (human assets) determines a startup's value creation. We begin with a simple formal model to examine the subtle yet crucial interplay between allocation of resources and uncertainty in technology startups.

We focus on market uncertainty about consumer demand for a new technological product.

[5] Marc Andreessen from Andreessen-Horowitz has been worried that high burn rate startups are at high risk of failure (`https://money.cnn.com/2014/09/25/investing/marc-andreessen-startup-warning/index.html`, accessed March 17, 2021).

Uncertainty is one crucial dimension that differentiates the strategic decision-making of high-tech, research-intensive entrepreneurial firms from established firms and non-tech small firms. In our model, an entrepreneur decides how to allocate resources to research and develop the product when facing uncertainty about demand. The entrepreneur has access to a technology f that combines labor and non-labor inputs. We denote x the share of a budget allocated to labor. The budget is normalized to 1, and we focus on the case in which the budget constraint binds as it is a documented feature of most startups (e.g., Stevenson et al. 1999). Thus, $1 - x$ corresponds to the share allocated to non-labor inputs. This setup has two simplifying assumptions to make the analysis parsimonious. First, we assume that the firm spends its entire budget. This is not a limiting assumption because the budget's portion unspent on human assets can be considered part of the non-labor investment allocation. Second, the normalization of the budget to 1 is without loss of generality because our focus is on each firm's tradeoff between the returns to labor and non-labor inputs, not on how two firms with different budgets allocate resources.

We assume that a product is developed using a technology f that combines labor and non-labor inputs as follows:

$$f(x) = \lambda x + \kappa(1 - x),$$

where λ and κ are such that $\lambda > \kappa > 0$ and represent the relative productivities of labor and non-labor inputs, respectively. Labor being more productive than capital captures the importance of talent in entrepreneurial firms (e.g., Wasserman 2012, Roach and Sauermann 2015, Choi et al. 2023, Hietaniemi et al. 2024). The linear production function captures, in a simple way, our focus on resource allocation and can be interpreted as the level of product development attained by a given combination of labor and non-labor inputs. The assumption that labor is more productive than non-labor spending, $\lambda > \kappa > 0$, implies that $f(x)$ is strictly increasing in the labor share x. An interpretation of this assumption is that a more developed product requires increased spending on human assets (salaries or employees) relative to non-human assets, reflecting, for example, the importance of intangible value brought in by human talent (e.g., Ganco et al. 2019).

Highly developed products are not necessarily preferred to less developed ones. Ample evidence documents that demand can exist for simpler, smaller, and more convenient products to use even when more complex and developed versions exist. For instance, the idea of "disruptive innovation" is centered on entrants offering a product with inferior quality compared to that of an incumbent, but one that serves a niche market unaddressed by the incumbent's product (Christensen 1997, Rosenbloom and Christensen 1994). To capture this tension, we assume that a given product $f(x)$ may or may not meet enough demand. The entrepreneur, therefore, faces a trade-off: to launch a less developed product that is likely to face demand but generate a lower value from it or an over-engineered product that might capture higher value but that consumers might not find desirable.[6] The less developed product forgoes potential revenues when demand is high, and an over-engineered product can fail if demand is insufficient.

Denoting the realized market demand for the product as d, the value v a firm captures depends on both the demand and the labor share x of the budget as follows:

$$v(x) = \begin{cases} f(x) & d \geq f(x) \\ 0 & d < f(x). \end{cases}$$

Note the expression assumes that if demand is below the development level $f(x)$, then the product has zero scrap value or the firm has high adjustment costs when $d < f(x)$. This

[6] A close interpretation is the idea that entrepreneurial firms conducting experiments may want to identify, develop, and commercialize a minimal workable version of the product that reveals whether there is demand for it (e.g., Kerr et al. 2014, Ewens et al. 2018). However, the idea of a minimum viable product (MVP) differs from that represented by the product development function $f(x)$ in that firms launching MVPs care about demand learning to inform future decisions while we are concerned with resource allocation to capture value from demand.

is to ease exposition. Assuming a positive constant scrap value does not change the main results in the paper.

When choosing its labor allocation x, the future demand d is unknown and uncertain. We assume that the entrepreneur has prior knowledge (or a belief) about the likely realization of d. In our model, d is uniformly distributed over the interval $[d_0 - \Delta, d_0 + \Delta]$, where d_0 is a positive location parameter large enough to avoid negative realizations of demand, and Δ is a positive parameter that captures the degree of uncertainty about the eventual demand realization.

Because of the uncertainty in d, the firm cannot choose a priori the optimal share of labor spending x; it can only choose x to maximize the expected value of $v(x)$, which is

$$E(v(x)) = \int_{f(x)}^{d_0+\Delta} \frac{f(x)}{2\Delta} dz = f(x) \left(1 - \frac{f(x) - (d_0 - \Delta)}{2\Delta}\right) \tag{1}$$

over $x \in [0, 1]$. Equation 1 takes an intuitive form: the level of product development $f(x)$ times the chance that there is demand for such a product. Equation 1 makes explicit our interest in studying how the firm's decision-maker deals with uncertainty because it leaves out the two cases that would render the problem trivial. The first case is when the lowest possible demand is larger than the most developed product attainable. In such a case, the problem does not involve uncertainty and not knowing the demand does not affect the firm's behavior. The firm produces the most developed product it can regardless of uncertainty. The second case is when the highest possible demand is too low for the firm to want to produce anything. Again, demand uncertainty does not affect the firm's behavior, which would be simply not to produce anything. Thus, we focus on the relevant case when the firm's capability, which extends from the lowest possible production $f(0) = \kappa$ to the highest one $f(1) = \lambda$, overlaps with the set of potential demand realizations $[d_0 - \Delta, d_0 + \Delta]$.[7]

[7] The values for these ranges appear with the results in Proposition 1.

Equation 1 features two additional elements. First, it depends directly on demand uncertainty, represented by Δ. Increased Δ is associated with higher chances that there is demand for the product because there is a higher likelihood of extreme demands: the expression in parentheses is increasing in Δ, everything else being equal. For example, the skewness of outcomes such as revenue growth or innovation of technology startups is consistent with this specification (see, e.g., Puri and Zarutskie (2012), Guzman and Stern (2020)). Second, while increasing product development $f(x)$ increases the potential value captured by the firm, it also decreases the chances that there is enough demand for it. This trade-off leads to the first result. Proofs are in the Appendix.

Proposition 1. *Consider the parameters $\lambda > \kappa > 0$ (labor is more productive than non-labor) and $\Delta > d_0/3$ (uncertainty is not too low).*

- *The unique labor share x^* in $[0,1]$ that maximizes the expected value for the entrepreneur is given by*

$$x^* = \frac{d_0 - 2\kappa}{2(\lambda - \kappa)} + \frac{1}{2(\lambda - \kappa)}\Delta, \tag{2}$$

  when parameters are such $2\kappa - d_0 < \Delta < 2\lambda - d_0$, describing an interior solution. The level of product development at the labor share x^* is $f(x^*) = (d_0 + \Delta)/2$.

- *The firm invests the whole budget on labor, namely $x^* = 1$, when $2\lambda - d_0 < \Delta$. The level of product development then is $f(1) = \lambda$.*

- *The firm does not invest in labor, namely $x^* = 0$, when $\Delta < 2\kappa - d_0$. The level of product development then is $f(0) = \kappa$.*

Note that Proposition 1 requires order in the productivity parameters $\lambda > \kappa > 0$, and an uncertainty parameter larger than a threshold that depends on the expected demand: $\Delta > d_0/3$. The conditions on the productivity parameters highlight the assumption that human talent drives product development, as it is the basis for creative, intangible, and tacit knowledge. The condition on demand uncertainty allows us to focus on the relevant cases where product development lies within the possible demand levels.[8] In what follows, we focus on interior solutions given by the first item in Proposition 1.

The uniqueness result of Proposition 1 provides two valuable insights. The first one is about failure rates, which we use in the empirical application as a measure of uncertainty below. The failure rate can be defined as the chance that the chosen product development level does not meet enough demand, i.e., that $Pr(f(x^*) > d)$. The failure rate can be written as $(f(x^*) - (d_0 - \Delta))/2\Delta$. Because the failure rate is directly associated with demand uncertainty Δ, it can be used as an empirical proxy for demand uncertainty. Plugging in x^* from Equation 2 into the expression for failure rate yields $3/4 - d_0/(4\Delta)$, which increases with demand uncertainty Δ. This is also consistent with Wu and Knott (2006).

The other insight from Proposition 1 is about the effect of uncertainty on labor share. By inspecting Equation 2, an increase in demand uncertainty Δ must be compensated by the firm choosing a larger labor share x^* to keep the equality. This positive relationship can be formalized as follows.

Corollary 1. *The interior labor share chosen by the entrepreneur is unique and increases in demand uncertainty.*

The logic underlying Corollary 1 is that higher uncertainty increases the chance of high demand, incentivizing the firm to pursue more developed products. More developed products require more labor because labor is the most productive input. Our first hypothesis is the direct application of Corollary 1.

Hypothesis 1. *Increased uncertainty is associated with increased labor share.*

[8] A sufficient condition for the chosen level of product development to lie within the feasible demand levels is that $f(x^*) = (d_0 + \Delta)/2$ is greater than the lowest possible demand realization $d_0 - \Delta$, which is equivalent to $\Delta > d_0/3$.

3.1 Uncertainty, quality, and quantity of workers

The positive relationship between uncertainty and labor share implies that uncertainty cannot negatively impact both the quality and quantity of workers. To see this, note that labor share can be written as the product of average wages w^* and number of workers L^*, $x^* = w^* L^*$. Wages measure the quality of the workforce because higher wages attract more talented, motivated, or committed workers. By Corollary 1,

$$\frac{dx^*}{d\Delta} = L^* \frac{dw^*}{d\Delta} + w^* \frac{dL^*}{d\Delta} > 0,$$

which occurs if uncertainty has a positive relationship with at least one, quality and quantity, and either a positive or a not-so-negative relationship with the other. Whether any of these relationships between uncertainty, quality, and quantity holds is an empirical question, stated in the following hypotheses.

Hypothesis 2a. *Increased uncertainty is associated with increased workers' quantity.*

Hypothesis 2b. *Increased uncertainty is associated with increased workers' quality.*

3.2 Performance implications of uncertainty, quality, and quantity of workers

Uncertainty's effect on the labor share has performance implications. The most evident one is that firms make mistakes. All firms except the lucky ones for which the realization of demand coincides with their chosen level of product development $f(x^*)$ allocate too little or too much of their budgets to labor, which reduces their performance relative to the no-uncertainty optimal performance. We state this baseline effect of uncertainty as an empirical hypothesis:

Hypothesis 3. *Extreme labor shares are associated with worse firm performance than* *moderate labor shares.*

Without uncertainty, the firm would pick labor share x that equates to the level of product development $f(x)$ and the demand d for it, making no mistakes: $f(x) - d = 0$. Uncertainty, however, makes the error different from zero in general. For example, we can show that the expected quadratic error $E[(f(x^*) - d)^2]$ equals $(3d_0^2 - 6d_0\Delta + 7\Delta^2)/12$, an expression that is increasing in demand uncertainty if Δ is not too low: $\Delta > 3d_0/7$.[9] Thus, we should expect deviations from the no-uncertainty optimum to increase in the uncertainty parameter Δ for high-tech entrepreneurial firms, which usually operate in high-uncertainty environments. We lay out such an effect of uncertainty on performance in the following hypothesis.

Hypothesis 4. *Increased uncertainty is associated with performance farther from the no-uncertainty optimum (inefficiency).*

The model prescribes how the firm allocates labor spending to achieve some desired level of product development. This determines the unique spending on labor in Equation 2. However, the firm is indifferent as to whether labor spending is achieved with more or better (paid) workers as long as the level of product development remains the one that maximizes its expected profits. Because product development is unchanged, so is inefficiency. This observation yields our final hypotheses.

Hypothesis 5a. *Increased quantity of workers is not associated with performance closer to the no-uncertainty optimum.*

Hypothesis 5b. *Increased quality of workers is not associated with performance farther from the no-uncertainty optimum.*

[9]Note that $3d_0/7 > d_0/3$, so the cases in which uncertainty increases the expected quadratic error are also cases in which Proposition 1 holds.

4 Data and Empirical Methodology

We empirically test the predictions about the relationship between human and non-human resource allocation and firm performance using the Annual Survey of Entrepreneurs (ASE). The ASE is a nationally representative survey conducted by the US Census Bureau (Foster and Norman 2016). The ASE was launched in 2014 to survey roughly 290,000 business startups on an annual basis. The ASE contains a set of repeated questions along with a topical module that varies for each vintage year. The 2014 ASE is the only vintage in which respondents were asked about spending decisions (i.e., allocation between human and non-human assets) in their R&D efforts. Therefore, we base our analysis on the startups that were included in the 2014 ASE. Furthermore, the 2014 ASE is ideal for studying technology startups in our context, as survey questions on resource allocation are based on R&D expenditures. We exclude firms that do not conduct R&D.

We integrate this survey with the Longitudinal Business Database (LBD), which is a comprehensive dataset of all establishments in the U.S. economy with at least 1 employee (Jarmin and Miranda 2002). The LBD assigns each establishment with a unique identifier such that it can be longitudinally tracked even after firm ownership changes (e.g., acquisitions). From the LBD, we extract information about each firm including its NAICS-based industry, geographic location, employment, and revenues.

Our final sample contains 6,100 startup firms. As shown in Table 1, firms in our sample are expectedly both young and small, with an average age of 6 years and size of 64 employees. Though all of these firms are R&D active with an average annual spending of roughly $2.1M, there is a significant variation with a standard deviation of $76.2M. On average, the allocation of R&D spending on labor (i.e., labor share) is 41%.

[Table 1 about here.]

Our sample of R&D-active startups represents many industries. Table 2 shows the list of two-digit NAICS industries along with their sample share and mean R&D labor share. The top three industries represented are Professional, Scientific, and Technical Services (24% of the sample); Manufacturing (14%); and Health Care and Social Assistance (12%). There is heterogeneity in mean R&D labor share across industries. Information (NAICS 51) and Professional, Scientific, and Technical Services (NAICS 54) have the highest average labor share in R&D, 62% and 57% respectively, while Accommodation and Food Services (NAICS 72) and Real Estate and Rental and Leasing (NAICS 53) have the lowest average labor share in R&D, 17% and 19%, respectively.

[Table 2 about here.]

4.1 Key Variables

We describe the measurement of our main dependent and independent variables.

Firm Performance. We use the LBD to measure firm performance across several measures as our dependent variable. First, we measure failure as a binary variable equaling one if none of a firm's establishments identified in 2014 (i.e., the year of the survey) are active (i.e., at least 1 employee on payroll) in 2016. Second, we measure employment growth as the percent change in the number of employees between 2014 and 2016 using the LBD. Third, we construct a similar measure of revenue growth as the percent change in sales between 2014 and 2016.[10]

R&D Labor Share. To capture how resources are allocated between human and non-human assets, we measure R&D labor share as the percent share of R&D spending on labor relative to the total R&D spending. Based on the 2014 vintage of the ASE, R&D spending on labor consists of "employee payroll" while that on non-human assets includes "equipment purchases", "software and licensing purchases", and "other R&D expenses." Figure 1 shows

[10] As revenue information is not available for some firms in the LBD, analysis using revenue growth is therefore based on a smaller sample.

the questions from the 2014 ASE used in this study.

Demand Uncertainty. A central feature of our theory is that entrepreneurs must decide under uncertainty (Knight 1921). As Wu and Knott (2006) point out, high uncertainty associated with startups is accompanied by high rates of firm failure during this stage of the firm lifecycle. Therefore, we use firm failure rates in a specific domain to proxy for demand uncertainty. To capture how the level of uncertainty may vary, we measure prior failure rates in each industry $\times$ state market.[11] To guard against finding a mechanical effect, this measure is based on the three preceding years (i.e., 2010-2013) such that the focal firm is not included.

Labor Quantity and Labor Quality. We decompose R&D labor share into their two components—specifically, labor quantity and labor quality. Labor quantity is the log of the total number of paid R&D employees as recorded in the 2014 ASE.[12] We measure labor quality as the log of the average wages among the R&D personnel. Average wages are computed as the total R&D employee payroll divided by the number of paid R&D employees.

[Figure 1 about here.]

4.2 Empirical Methodology

We begin with a series of linear regressions to examine whether and how demand uncertainty is associated with firms' labor share, labor quantity, and labor quality. Then, we assess the relationship between labor share and firm performance by regressing firm outcomes—namely, firm failure, employment growth, and revenue growth—on the startup's percent share of R&D spending on human assets. Because our theory prescribes a non-linear relationship between

[11] As the size of industries can geographically vary (e.g., Semiconductor manufacturers in California versus Texas), we define market as the unique combination of industry, which is measured at the four-digit NAICS level, and state.

[12] Owners are included if the respondent reports them as R&D-performing employees. Unpaid workers and interns are not included in this measure.

labor share and firm outcomes, we use a quadratic function of labor share (i.e., linear and quadratic terms). As a baseline, we include state and industry fixed effects to account for idiosyncratic effects in each region and NAICS-4 industry.

Following the initial analysis that explores the relationship between firm-level outcomes and share of R&D spending on human assets, we proceed with a stochastic frontier analysis to estimate the association of R&D labor quantity and quality on firm inefficiency. Stochastic frontier analysis assumes that not all firms can allocate their resources optimally, allowing each firm to deviate from optimal allocation by an individual inefficiency margin. To perform the analysis, we estimate the following model:

$$y_i = \boldsymbol{\alpha} + \beta_1 LaborShare_i + \beta_2 LaborShare_i^2 + v_i - u_i \tag{3}$$

where y_i is the outcome we analyze (i.e., firm failure, % employment growth, or % revenue growth), $\boldsymbol{\alpha}$ contains an intercept and fixed effects (i.e., state, industry, and firm age), $LaborShare_i$ is the R&D labor share of firm i, v_i is an idiosyncratic firm shock which is assumed to be normally distributed with mean zero, and u_i is the firm's inefficiency, which measures how far it is from allocating its resources efficiently.

The stochastic frontier model assumes that the most efficient firms have $u_i = 0$, while for others, their inefficiency drives the value of u_i. When the outcome is failure, higher values of y_i are worse, hence higher values of u_i are better. When the outcome is firm performance (such as revenue growth or employee growth), higher values of u_i are worse. The inefficiency is modeled as follows:

$$u_i = \alpha_u + \gamma_1 LaborQuantity_i + \gamma_2 LaborQuality_i + \gamma_3 DemandUncertainty_i + \epsilon_i,$$

where α_u is the inefficiency intercept, and ϵ_i is assumed to be half normal and can only take positive values.

By controlling for possible firm inefficiencies in resource allocation, the stochastic frontier analysis allows us to assess the tradeoff between allocation to R&D employees and non-human assets while determining the extent to which demand uncertainty, labor quality, and labor quantity are associated with inefficiency. The tradeoff between labor and non-labor assets would manifest in a U-shaped relationship between firm performance and allocation of R&D spending to labor across firms. The empirical role of the three aforementioned factors emerges through modeling the level of inefficiency u_i for each firm. In addition, by controlling for demand uncertainty as a source of inefficiency, we can learn whether hiring too many (or not enough) people or whether hiring people of higher quality (or under-investing in quality by recruiting low-paid workers) is a larger contributor to reduced firm performance.

5 Results

We begin by examining the relationship between demand uncertainty and labor share. We use linear regression to predict labor share as a function of demand uncertainty in the underlying market, defined at the industry $\times$ state level. Specification 1 of Table 3 shows a strong positive association ($p < .01$). In markets with higher levels of demand uncertainty, firms tend to allocate higher share of R&D expenditures to labor. In specification 2, when we control for firm size, age, and the underlying state and industry, we find that the positive relationship remains robust ($p < .01$). A one standard deviation increase in demand uncertainty is associated with a two percentage point increase in labor share. Relative to the baseline mean of labor share at 40%, this association represents a 5% increase. The results are consistent with Hypothesis 1, which states that increased demand uncertainty is linked to higher labor share.

We next explore whether demand uncertainty is associated with labor quantity and labor quality. In specification 3, demand uncertainty and labor quantity are positively albeit weakly related ($p = .07$). This positive relationship is more precise when we add controls in specification 4 ($p < .01$). A one standard deviation increase in demand uncertainty is associated with an increase of roughly one additional employee. In contrast, we do not find a meaningful relationship between demand uncertainty and labor quality in specifications 5 and 6 ($p = .22$ and $p = .39$, respectively). Together, these results imply that startups tend to hire more R&D workers—but not necessarily alter the quality of the workers they pursue—when facing higher levels of demand uncertainty. These patterns provide support for Hypothesis 2a, but not for Hypothesis 2b.

[Table 3 about here.]

We turn to assess the performance implications of labor share in a regression model that includes a linear term and a quadratic term of R&D labor share (*LaborShare*) as explanatory variables. Table 4 presents the analysis of the relationship between *LaborShare* and each of three outcomes: Firm failure, employment growth, and revenue growth. For firm failure, we observe that the $LaborShare$ coefficients are both significantly different than zero at conventional levels. The coefficient on the linear term is negative, and the one on the quadratic term is positive in each specification (1) and (2). Firm failure is a negative outcome, so these results are consistent with extreme labor shares associated with more failure: a U-shaped relationship between labor share and firm failure as predicted by the theory. The point estimates from specification (1) give us an idea of the labor share that minimizes the probability of failure by computing the minimum point of the quadratic parabola. The minimum is at $0.179/(2 \times 0.142)$, equivalent to a 63% share of R&D expenditures allocated to labor. This exercise is not meant to prescribe an optimal labor share for each firm in each industry; rather, it proves helpful as a point of comparison. For example, the high labor share implied by the point estimates contrasts with the mean of 41% across all firms in our data. Notably, the share of 63% is very close to the observed share of R&D labor share in the

Information, and the Professional, Scientific, and Technical Services sectors. Controlling for firm size and firm age does not alter the results substantially. These patterns are consistent with our Hypothesis 3.

For employment growth and revenue growth outcomes, we expect to find an opposite direction for the $LaborShare$ coefficients. Such an inverse U-shaped effect would indicate that extreme labor shares are associated with lower values of these outcome variables. Indeed, we observe that the coefficients are reversed in signs for these outcome variables. As before, we can use the coefficients to estimate the value of $LaborShare$ where the outcome variables are maximized. The value is 56% for employment growth (specification 3) and 46% for revenue growth (specification 5). Despite the fact that firm failure and employment growth are measured in different units, we observe that the optimal R&D labor shares for failure and employment growth are relatively close. However, the R&D labor share has a somewhat different association with firm failure than with revenue growth, as seen in the 17% difference between their optimal allocations. In any case, the fact that each specification features a significant quadratic relationship in the way prescribed by our Hypothesis 3 suggests that our resource allocation model has empirical support.

[Table 4 about here.]

We now proceed to the stochastic frontier analysis. Table 5 presents the results. Recall that the stochastic frontier analysis allows us to control for the effect of individual firm inefficiencies caused by misallocation of R&D resources. The results from the quadratic model show similar patterns to those in the linear regressions in Table 4, except for one important difference. The similarities are worth highlighting first. We see a U-shaped relationship between labor share and firm failure in specifications 1 and 2, and between labor share and employment growth in specifications 3 and 4. However, the relationship seems noisier for employment growth in this case than in the regression models in Table 4. The estimated optimal allocations of R&D labor share for firm failure and employment growth are relatively similar, with values of 60% and 53% respectively. The difference between the stochastic frontier analysis and the previous regression analysis emerges from the revenue growth in specifications 5 and 6 of Table 5. Both parameters of interest, namely the one accompanying the linear and squared labor share variables, are imprecisely estimated. The estimated optimal R&D labor share for revenue growth is down to 39%. This suggests that we should take with caution the relatively low optimal labor share of 46% inferred from specifications 5 and 6 in Table 4.

Next, we transition to studying three factors— specifically, demand uncertainty, labor quantity, and labor quality—as potential sources of firm efficiencies in their R&D resource allocation to labor. Recall that given that the outcome variable is failure, negative values of u_i in equation 3 indicate attainment of lower efficiency. As displayed in specifications 1 and 2, demand uncertainty is associated with lower firm efficiency ($p = .02$ and $p = .01$). For employment growth as the outcome, a positive sign in the coefficient indicates efficiency losses. In specifications 3 and 4, we find a positive estimate accompanying uncertainty, though the former is less precisely estimated ($p = .12$ and $p = .05$). Similarly, demand uncertainty exhibits a positive estimate for revenue growth in specifications 5 and 6 ($p < .01$ and $p < .01$). Across the three performance outcomes, demand uncertainty is linked to greater inefficiencies in the performance relationship between labor share, lending support to Hypothesis 4.

Furthermore, we examine labor quality and quantity as sources of inefficiency in firm performance. For firm failure, the quantity of employees is associated with increased firm efficiency. In both specifications 1 and 2 for firm failure, the coefficient on quantity is large and precisely estimated ($p < .01$ and $p < .01$). Quality, however, does not seem to be associated with efficiency gains. The coefficient accompanying quality is small and imprecisely estimated in each of those specifications in Table 5 ($p = .64$ and $p = .39$).

For employment growth, we see that both coefficients, the one on quantity and the one on quality, feature negative signs in specification 3 (p = .01 and p = .33). But only the coefficient accompanying quantity is large and precisely estimated. The same qualitative result holds in specification 4 (p < .01 and p = .26). Similar results appear for revenue growth in specifications 5 (p = .01 and p = .92) and 6 (p < .01 and p = .56). Taken together, the findings from the inefficiency model in Table 5 suggest that hiring too few workers seems to be associated with greater inefficiency. All in all, firms that hire many workers seem to attain efficiency gains with respect to other firms that hire too few, which does not support Hypothesis 5a. This scale effect is similar to the one found in Chen et al. (2015) for the case of factory production scale. However, our Hypothesis 5b is borne out by the data. Efficiency does not seem to be associated with hiring high-quality workers.

[Table 5 about here.]

6 Conclusion

Hiring is a critical decision for technology startups because each new hire represents a relatively large addition given their small size. However, hiring exceptional talent is costly and inevitably reduces resources that can be spent on non-human assets. This hiring challenge is especially severe for startups because their nascent products face heightened uncertainty regarding consumer demand. In this paper, we theoretically model this tradeoff under demand uncertainty and provide empirical evidence based on innovation-driven startups surveyed by the US Census. We find that with higher levels of demand uncertainty, startups tend to allocate a greater share of their resources to labor. This increased focus on labor is driven by hiring more workers rather than by pursuing higher-quality workers. In terms of performance implications, we find an inverted U-shape relationship between R&D resource allocation in human capital and firm performance; that is, firm performance rises with greater allocation of resources to human capital up to a certain point, after which it falls as startups over-allocate resources towards labor. In addition, we find that the inefficiency in hiring decisions for R&D-active startups stems more from the under-hiring of employees ("quantity") and less from the wage levels paid to employees ("quality").

6.1 Contributions

Studying resource allocation under demand uncertainty leads to three main contributions. First, we contribute to the literature on strategic human capital which has identified the importance of human assets for firm performance (e.g., Coff 1997, Unger et al. 2011, Campbell et al. 2012, Sakakibara and Balasubramanian 2020). We extend this perspective by situating human capital as one input in a resource allocation framework. In other words, we demonstrate that prioritizing hiring can be at the expense of non-human assets. Our findings show that an imbalance between the two can diminish firm performance.

Second, we contribute to the resource allocation literature by focusing on technology startups, which have received less attention largely due to a lack of available data. Technology startups present an important context in advancing our understanding of resource allocation as these firms are mostly single-unit businesses that are structurally limited in their ability to redeploy resources (Belenzon et al. 2019, Lovallo et al. 2020). As a result, initial resource allocation decisions are likely to have an amplified impact on these technology startups' performance—likely contributing to the high failure rates in entrepreneurship (e.g., Stinchcombe 1965, Choi et al. 2023).

Third, we contribute by examining investments in human assets by their two components—namely, quantity and quality. Extending prior work showing the importance of star employees (e.g., Groysberg et al. 2008), we highlight the tradeoff between hiring the "best" versus "more" employees. We find that quantity is a significant contributor to inefficiencies in labor allocation decisions.

6.2 Managerial Implications

Hiring is a key managerial challenge for startups. For instance, in a series of surveys administered by First Round Capital, founders of venture-backed startups consistently report "hiring good people" as the top concern for their ventures among other factors such as fundraising, revenues, and competition.[13] As startups tend to make hiring decisions in the midst of uncertainty regarding the market demand for their product (e.g., Hietaniemi et al. 2024), hiring is inevitably a difficult task for startups.

Practically, there are approaches that startups can pursue while hiring under uncertainty. One common path is to under-hire and postpone further hiring until product demand is actually realized. Our study cautions against this approach of under-hiring. While over-hiring can also dwindle firm performance by allocating resources to unnecessary talent, our results show that much of the inefficiency in hiring stems from startups that under-allocate their spending towards labor. In contrast, we do not find any evidence that wage levels contribute to hiring inefficiencies. In other words, while expensive, hiring high-wage workers does not appear to negatively impact startup performance.

6.3 Limitations and Future Work

This study relies on cross-sectional survey data on startups' R&D resource allocation decisions, which are then linked to ensuing performance outcomes. However, resource allocation can be viewed as a dynamic process in which managers make such decisions on a quarterly or annual basis. This perspective is especially salient for established firms with a track record from which they can learn (e.g., Cohen and Levinthal 1990, Balasubramanian and Lieberman 2010). This raises an important question for future research: To what extent do firms learn from their prior resource allocation decisions in hiring, and what facilitates or hampers this

[13] For the full survey results, see `https://stateofstartups.firstround.com/2016`, accessed March 17, 2021.

learning?

In addition, we are able to observe human capital characteristics at the firm level but not at the individual level. Therefore, we cannot distinguish the roles of the startups' R&D personnel (e.g., managers versus engineers). This raises the question on how the role composition of startup teams can influence the consequences of resource allocation decisions. For example, if managers possess skills that are more easily transferable to non-R&D parts of the firm, then over-hiring these individuals can mitigate detrimental effects of suboptimal resource allocation decisions due to the benefits of resource deployability (e.g., Belenzon and Tsolmon 2016, Hietaniemi et al. 2024). Therefore, future research can examine how the distinct roles can shape the redeployability of human resources and, thus, the calculus in resource allocation decisions.

Finally, by focusing on the consequences of resource allocation between human and non-human assets, this study does not speak much to the antecedents beyond the fundamental role of demand uncertainty. While we document significant industry-level variation in R&D labor share, which likely reflects the capital intensity of the underlying industry, it remains unclear what organizational or individual factors can endogenously influence these resource allocation decisions. For instance, raising funding from external investors (e.g., venture capital) may skew the startup to over-allocate towards human assets in response to the investors' pressure for growth. At the individual level, serial entrepreneurs may more efficiently allocate resources by drawing on their prior experience. Broadly, future work can shed light on the antecedents to startups' spending decisions in human versus non-human assets.

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Figure 1: Questions from the ASE 2014 used in this paper as they appear in Foster and Norman (2016).

TOTAL R&D COST
In 2014, what was this business's **total cost** for R&D activities?
Include:

- Labor paid for employees, temporary staffing, contractors, independent contractors, or outside consultants
- Materials, equipment, software, or other supplies purchased
- Money spent for rent, utilities or other overhead

$________________,000

BUSINESS R&D COSTS
In 2014, what percent of the costs of R&D services **performed by this business** consisted of the following purchase?
Note: To calculate R&D services performed by this business, subtract the Purchased R&D costs from the Total R&D costs.
Round to the nearest whole percent. Your best estimate is fine. If none, report "0."

Employee payroll	____%
Equipment purchases	____%
Software and licensing purchases	____%
Other R&D expenses	____%
Total	**100%**

NUMBER OF R&D EMPLOYEES
For the pay period including March 12, 2014, how many of each type of the following workers worked on R&D activities?

	Number of workers
Owner(s)	____
Paid Employees	____
Other Paid Workers - *Include labor paid for temporary staff, contractors, independent contractors, and outside consultants.*	____
Unpaid Workers/Interns	____

Notes: This figure shows the questions from the ASE 2014 used to obtain the key variables in this study: R&D labor share, Labor Quantity and Labor Quality.

Table 1: Summary Statistics

Variable	**N**	**Mean**	**SD**
Firm age (Years)	6,100	6	4.4
Firm size (Total employees)	6,100	64	370
Total payroll ($ thousands)	6,100	6,640	75400
Revenues ($ thousands)	4,200	19,400	142,000
R&D spending: Total ($ thousands)	6,100	2,160	76,200
R&D spending: % Labor share	6,100	0.41	0.38
R&D employees	6,100	16	148
R&D average wages ($ thousands)	6,100	114	538
State = California	6,100	0.14	0.34
State = Texas	6,100	0.06	0.25
State = New York	6,100	0.06	0.23
State = Florida	6,100	0.06	0.23
State = Massachusetts	6,100	0.03	0.18
State = Others	6,100	0.65	0.48
Firm failure (by 2016)	6,100	0.145	0.352
% Employment growth (2014-2016)	6,100	0.048	0.808
% Revenue growth (2014-2016)	4,200	0.158	0.774
Demand uncertainty	6,100	0.067	0.025

Notes: This table presents summary statistics at the firm level. Counts are rounded according to Census disclosure rules. The sample consists of firms in the 2014 vintage of the Annual Survey of Entrepreneurs conditional on being R&D active. Firm-level characteristics are based on 2014, except for performance measures (e.g., firm failure, employment growth, and revenue growth), which use information from 2016. As revenue information is not available for some firms in the Longitudinal Business Database, firm counts are lower for *Revenue Growth*.

Table 2: Industries Represented in the ASE 2014 Sample

Sector Name	**Firms**	**Labor Share**	**Spend ($th)**	**Employees (Average)**	**Wages ($th)**
Construction	7%	24%	12,300	7	120
Manufacturing	14%	48%	840	19	110
Wholesale Trade	8%	48%	7,470	14.1	130
Retail Trade	7%	27%	950	6.2	80
Transportation and Warehousing	2%	29%	970	5.3	70
Information	4%	62%	490	73.8	200
Finance and Insurance	2%	39%	910	11.3	150
Real Estate and Rental and Leasing	2%	19%	1,340	3.8	80
Professional, Scientific, & Technical Svcs.	24%	57%	380	23	90
Admin., Support, Waste Mgmt, & Remediation Svcs.	5%	33%	1,020	16.9	160
Educational Services	1%	45%	840	9	150
Health Care and Social Assistance	12%	36%	640	7.8	130
Accommodation and Food Services	5%	17%	1,350	5.1	120
Others	6%	30%	1,020	7.4	110

Notes: This table shows summary statistics for firms in each sector (i.e., two-digit NAICS industry). Counts are rounded according to Census disclosure rules. *Labor Share* is the percent share of R&D spending on employee payroll. *Spend* is the total R&D expenditures denominated in thousands of dollars. *Employees* is the mean number of R&D employees. *Wages* is the mean annual wages of the R&D personnel. Sectors containing less than 1% of the sample are grouped into *Others*.

Table 3: Regression Estimates of Demand Uncertainty on R&D Labor

Dependent variable:	R&D Labor Share		Labor Quantity		Labor Quality	
	(1)	(2)	(3)	(4)	(5)	(6)
Demand uncertainty	0.724	0.771	1.156	1.774	-2.500	-1.692
	(0.219)	(0.218)	(0.645)	(0.619)	(2.031)	(1.982)
Log(firm size)		0.022		0.327		0.406
		(0.003)		(0.013)		(0.029)
State FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Firm age FE		X		X		X
Observations (firms)	6100	6100	6100	6100	6100	6100
R^2	0.139	0.149	0.093	0.274	0.049	0.079

Notes: This table presents cross-sectional linear regressions estimating the effect of demand uncertainty on startups' labor allocation decisions. Counts are rounded according to Census disclosure rules. The main explanatory variable *Demand uncertainty* is the rate of firm failure in the focal firm's industry × state market in the three preceding years. Labor allocation decisions are measured in three ways: First, *R&D Labor Share* is the percent share of R&D spending in 2014 on employee payroll. Second, *Labor Quantity* is the log number of R&D employees. Third, *Labor Quality* is the average annual wages of the R&D employees in 2014. Robust standard errors are shown in parentheses.

Table 4: Regression Estimates of R&D Labor Share on Firm Performance

	Dependent Variable:					
	Firm Failure		**% Employ. Growth**		**% Revenue Growth**	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D Labor Share^2	0.142	0.150	-0.453	-0.434	-0.396	-0.361
	(0.048)	(0.047)	(0.114)	(0.114)	(0.130)	(0.130)
R&D Labor Share	-0.179	-0.170	0.510	0.497	0.361	0.330
	(0.046)	(0.045)	(0.107)	(0.107)	(0.121)	(0.120)
Log(firm size)		0.034		0.002		0.009
		(0.003)		(0.007)		(0.008)
State FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Firm age FE		X		X		X
Observations (firms)	6100	6100	6100	6100	4200	4200
R^2	0.021	0.054	0.018	0.029	0.034	0.054

Notes: This table presents cross-sectional linear regressions estimating the effect of R&D labor share on startup firm performance. Counts are rounded according to Census disclosure rules. The main explanatory variable *R&D Labor Share* is the percent share of R&D spending in 2014 on employee payroll. Dependent variables on startup firm performance are based on values in 2016. Specifically, *Firm Failure* is a binary variable equaling one if the firm was associated with zero employees in 2016. *Employment Growth* and *Revenue Growth* are the percent change in employment and revenue, respectively, between 2014 and 2016. Robust standard errors are shown in parentheses.

Table 5: Stochastic Frontier Analysis of R&D Labor Share

	Dependent Variable:					
	Firm Failure		**% Employ. Growth**		**% Revenue Growth**	
	(1)	(2)	(3)	(4)	(5)	(6)
Production Function model						
R&D Labor Share^2	0.134	0.119	-0.314	-0.292	-0.290	-0.241
	(0.048)	(0.048)	(0.125)	(0.125)	(0.136)	(0.135)
R&D Labor Share	-0.161	-0.150	0.331	0.315	0.229	0.185
	(0.046)	(0.046)	(0.122)	(0.121)	(0.131)	(0.129)
Constant	0.188	0.128	0.010	0.250	-0.046	0.317
	(0.080)	(0.080)	(0.162)	(0.176)	(0.181)	(0.191)
Inefficiency model						
Demand uncertainty	-19.8	-18.06	9.20	9.75	25.8	21.64
	(8.223)	(6.784)	(5.957)	(4.891)	(6.472)	(5.258)
Log(R&D employment) "quantity"	0.610	0.670	-1.734	-1.540	-2.496	-2.071
	(0.083)	(0.068)	(0.669)	(0.496)	(0.952)	(0.674)
Log(R&D average wages) "quality"	0.044	0.068	-0.043	-0.044	0.009	-0.036
	(0.096)	(0.079)	(0.045)	(0.039)	(0.087)	(0.061)
Constant	-7.489	-7.699	-2.784	-2.757	-5.084	-4.232
	(0.980)	(0.789)	(0.770)	(0.639)	(1.664)	(1.084)
State FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Firm age FE		X		X		X
Observations (firms)	6100	6100	6100	6100	4200	4200
Log likelihood	-2160	-2210	-7460	-7430	-4750	-4710

Notes: This table presents regression results from stochastic frontier analysis. Counts are rounded according to Census disclosure rules. The main explanatory variable in the production function model, *R&D Labor Share*, is the percent share of R&D spending in 2014 on employee payroll. Dependent variables on startup firm performance are based on values in 2016. Specifically, *Firm Failure* is a binary variable equaling one if the firm is associated with zero employees in 2016. *Employment Growth* and *Revenue Growth* are the percent change in employment and revenue, respectively, between 2014 and 2016. In the inefficiency model, *Demand uncertainty* is the rate of firm failure in the focal firm's industry $\times$ state market in the three preceding years. *Quantity* is the log number of R&D employees while *Quality* is the average annual wages of the R&D employees in 2014. Robust standard errors are shown in parentheses.

Appendix: Proofs

Proof of Proposition 1. First order condition:

$$(d_0 + \Delta)f'(x) - 2f(x)f'(x) = 0,$$

which, given the linearity of f, is equivalent to

$$f(x^*) = \frac{\Delta + d_0}{2}.$$

For entrepreneurs to face decisions under uncertainty, it must be the case that the marginal benefit for the entrepreneur to invest slightly above the minimum possible demand $d_0 - \Delta$ to be strictly positive, otherwise, it would be convenient for the entrepreneur to invest at the top of its capability regardless of uncertainty. This is equivalent to

$$f(x^*) = \frac{\Delta + d_0}{2} > d_0 - \Delta \iff \Delta > \frac{d_0}{3},$$

which we take as an assumption. In such a case, the first order condition leads to

$$x^* = \frac{d_0 - 2\kappa}{2(\lambda - \kappa)} + \frac{1}{2(\lambda - \kappa)}\Delta$$

when x^* lies between 0 and 1. Given assumption $\lambda > \kappa > 0$, the interior solution condition is $2\kappa - d_0 < \Delta < 2\lambda - d_0$. The second order condition

$$(d_0 + \Delta)f''(x) - 2\left(f'(x)f'(x) + f(x)f''(x)\right) < 0$$

for all x ensures x^* is unique. If uncertainty is very low such that $\Delta < 2\kappa - d_0$, a marginal increase in labor share will reduce $E(v(x))$, so the best the entrepreneur can do is to set

$x^* = 0$. In contrast, when $2\lambda - d_0 < \Delta$, the entrepreneur invests all their budget in labor: $x^* = 1$. $\square$

Proof of Corollary 1. This follows directly from differentiating Equation 2 with respect to Δ and noting that $2\kappa - d_0 < \Delta < 2\lambda - d_0$ implies $\kappa < \lambda$. $\square$