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Original Article

Whom do new firms hire?

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Abstract

Using the matched employer–employee data set for Denmark and information on the founders of new firms, we analyze the hiring choices of all new firms that entered from 2003 to 2010. We develop a theoretical model in which the quality of a firm's employees determines its average cost, a firm's productivity is based on its pre-entry experience and persistent shocks, and over time firms learn about their productivity. The model predicts that more productive firms are larger and hire more talented employees, which gives rise to various predictions about how pre-entry experience, firm growth rates, and firm size influence the wages firms pay to their early hires. We find that beginning with the time of entry, larger firms consistently pay higher wages to their new hires. These are firms with greater survival prospects at the time of entry based on the pre-entry backgrounds of their founders and that grow at greater rates over time, both of which are predictive of the wages paid to new hires from the time of entry onward. Our findings suggest workers are allocated to firms according to their abilities, which can give rise to enduring firm capabilities.

JEL classification: D21, J30, L25, L26

1. Introduction

We tend to associate new firms with their founders, and usually with a single individual who takes the lead in the formation of the firm. One of the earliest tasks of the founder is to recruit others to join him to get the firm going. No doubt this is a key step in the life of a new firm. In reflecting on his entrepreneurial initiatives, Gordon Moore, the cofounder of Fairchild Semiconductor and later Intel, had this to say about the early hiring decisions at Intel (Moore, 1994):

> From the beginning at Intel, we planned on being big. Since we had already been fairly successful at Fairchild, anything less successful in our new venture would have been a disappointment. So, at the very beginning we recruited a staff that had high potential and that we thought would be around to run the company for some time. . . . I think that people looking at start-ups, venture capitalists in particular, ought to push very strongly not to squander the opportunity to develop management during this time period.

Moore's remarks attest to the importance of the early hires of new firms. They also suggest that the prospects of new firms should influence the quality of their hires, and that these prospects are related to the experience and abilities of their founder(s). We know little, however, about the hiring practices of new firms. A series of studies on the hiring practices of a sample of high-tech start-ups in Silicon Valley indicates that the firms employed different kinds of hiring strategies, but no single strategy was superior (Baron and Hannan, 2002). Burton and Beckman (2007) also demonstrate that the initial individuals that firms hire for management positions can constrain them later and affect their performance. Studies focusing on the qualities of initial employees of start-ups are still relatively scarce (for a few exceptions, see e.g., Ruef *et al*., 2003; Ruef, 2010; Timmermans, 2010; Coad *et al*., 2014; Ouimet and Zarutskie, 2014). While these studies have focused on the early hiring decisions of new firms, we still know little about whether the prospects of firms when they enter condition the kinds of employees they hire.

The main purpose of this article is to exploit data from the matched employee–employer data set for Denmark to study the hiring choices of new firms. We can identify every new entrant in Denmark from 2001 to 2010 and every employee they hired through 2011. For each employee, we have data on their earnings in their first year at the new firm, their previous positions and earnings, their occupation, education, age, sex, and marital status. We also have detailed information about all the new firms, including the firm's likely founder, whether it incorporated, the number of years the firm survived, and the annual number of employees in the firm. We use the information about the likely founder and the firm at the time of entry to estimate the survival prospects of each firm and we use the employment data to compute the annual growth rates of each firm. Our analysis focuses on how the wages new firms pay to their hires at each age are related to their size and in turn their initial survival prospects and past annual growth rates.

We develop a theoretical model that provides a logical underpinning for Moore's observations. A firm's average cost is assumed to be determined by the quality of its employees, which implies that the value of a worker's marginal product depends on the size of the firm. New firms are assumed to differ from their outset regarding their productivity based on founding conditions and experience shocks to their productivity over time, which may have lasting effects. The model implies that more productive firms are larger and as a result hire better quality employees, which gives rise to various predictions about how the wages firms pay initially and over time to their new hires vary according to founding conditions, growth rates, and firm size.

We test these predictions on the hiring decisions of new firms through their first 8 years (or less) of life. In their year of entry, firms with founding conditions that are predictive of longer survival pay higher wages to their hires. In subsequent years, predicted firm survival and past firm growth rates consistently have a positive influence on the wages firms pay to new hires. Larger firms also consistently pay higher wages to their hires at each age. Part of the wage premium paid by larger firms and/or those with longer predicted survival and greater growth rates is due to such firms hiring individuals that are more educated and more highly paid in the past, but the estimated patterns persist even controlling for these factors. All of these patterns are consistent with the theory. When firm size is controlled, unexpectedly predicted survival and to some extent the most recent growth rates continue to positively influence the wages of new hires. We discuss and test various explanations for this finding.

Gordon Moore's remarks suggest that the early hiring decisions of new firms will importantly influence their performance and will be difficult to emulate or change when a firm is older. As such, the quality of the labor force assembled when a firm is young may serve as the basis for a firm capability. While all firms no doubt have access to talented workers, if the value of more talented workers depends on the size of the firm, then only superior firms would be able to profit from a strategy of hiring more talented workers. Judging from our findings, firms have an idea from the outset about their prospective performance based on the experience of their founders. This sets superior firms on a course regarding their size and the quality of their work force that cannot be profitably duplicated by lesser firms. Even if the original source of their advantage does not persist—for example, a distinctive founder no longer proves to be able to lead the firm once it grows bigger, as often occurs—under certain conditions the firm will retain an advantage related to its superior labor force. It is the match between the quality of the firm's labor force and its size that sustains its advantage and imparts a lasting capability.

Our theory and findings need to be considered in the context of the broader literature investigating regularities within industries between firm size and the wages and quality of employees. It is well established that within industries, larger firms employ more educated workers and pay higher wages (Oi, 1983; Oi and Idson, 1999). Various theories have been proposed to explain the regularities. Most recently, attention has focused on how differences in the productivity of labor associated with firm size may be key to explaining the regularities (Idson and Oi, 1999). Our theory is in this tradition, although it is not differences in the productivity of workers but rather the value of what they produce that is conditioned by the size of the firm. Cohen and Klepper (1996a,b) used a similar idea to explain variations within industries in the size and composition of firm R&D expenditures. We consider the ability of the alternative theories of the labor force-firm size regularities to explain our findings concerning new firms and the insights that can be gleaned from our findings concerning the forces underlying the regularities.

Our article is organized as follows. In Section 2 we present our model and derive various implications that we use to structure the analysis of the hiring decisions of new firms. In Section 3 we describe our data and present our empirical findings. In Section 4 we discuss the implications of our findings and possible alternative explanations for them. In Section 5 we offer concluding comments and discuss further possible investigations of the employment choices of new firms.

2. Theory

We propose a simple model composed of two parts: a model of employment choices for firms of different productivity, and a model of how firm productivity and growth evolve over time. The model considers only entrants and assumes that in every period the prospects for entry are the same, reflecting the simplifying assumption that over time price falls at the same rate as average cost. Predictions are derived concerning the hiring choices of new firms in their first year and then in subsequent years as they gain experience through production.

2.1 Firm production

To limit the size of firms in the model, we assume that production is subject to decreasing returns to scale. Diminishing returns are typically associated with the limited number of employees that managers can supervise. Accordingly, we distinguish between labor and nonlabor inputs and assume that labor is subject to diminishing returns. Similar to Lucas (1978) and Oi (1983), we assume that new firms differ in terms of the quality of their founders, which in turn gives rise to differences in their productivity. Let η_t denote the firm's productivity in period t, where $t = 1$ corresponds to the first period after entry.

Let Q_t denote the level of output of the firm in period t. To produce Q_t, the firm needs to hire labor to perform various tasks. Labor is assumed to come in two forms: ordinary labor and talented labor, with per unit costs of q and r, respectively, where $q < r$. Both types of labor are equally productive at the tasks required to carry out production. The total amount of ordinary and talented labor the firm needs to hire in period t to produce Q_t is specified as:

$$(L_t + T_t) \;=\; (Q_t/\eta_t)^{1/\alpha}, \tag{1}$$

where L_t and T_t are the amount of ordinary and talented labor hired in period t. It is assumed that $0 < \alpha < 1$ to reflect diminishing returns. The firm's productivity enters (1) multiplicatively and scales the amount of labor required to produce Q_t.

If the firm uses only ordinary labor, the cost per unit of output of the nonlabor inputs in period t is c_t, which is assumed to be independent of Q_t. Alternatively, if the firm hires talented labor, its cost per unit of output of the nonlabor inputs is $c_t - \beta T_t$, where $\beta > 0$. It is assumed that while performing the required tasks of production, talented labor develops insights into improving production that lower the average nonlabor costs by β for each unit of talented labor hired. To insure an interior solution for the output produced by the firm, if the firm uses talented labor, it is assumed that β is sufficiently small that the marginal cost of production is increasing in output over all relevant output levels. Further, we assume that after one period the improvements in production developed by all firms are costlessly imitated by every firm. This causes c_t to decline over time (for all firms) and limits the benefits of hiring talented labor to one period.

It is assumed that all firms are price takers and entry and exit are such that price falls over time by the decrease in c_t. Using equation (1), output can be expressed as $Q_t = \eta_t(L_t + T_t)^\alpha$ and the profits of the firm in period t can be written as $\pi_t = P_t\eta_t(L_t + T_t)^\alpha - (c_t - \beta T_t)\eta_t(L_t + T_t)^\alpha - (qL_t + rT_t) = (P + \beta T_t)\eta_t(L_t + T_t)^\alpha - (qL_t + rT_t)$, where $P \equiv P_t - c_t$ is constant over time. In each period, the firm chooses L_t and T_t to maximize π_t.

The optimal choices of L_t and T_t can be broken into two steps. First, given the optimal level of output, choose the profit-maximizing values of L_t and T_t. Second, expressing the choices of L_t and T_t as a function of the level of output, choose the level of output that maximizes profits. The first step has a simple corner solution. The total cost of production is $qL_t + rT_t + (c_t - \beta T_t)Q_t = qL_t + (r - \beta Q_t)T_t + c_tQ_t$. The net cost per unit of talented labor is $r - \beta Q_t$, which is a decreasing function of output, while the cost per unit of ordinary labor, q, is independent of output. Since ordinary and talented labor are interchangeable in production, it follows that total cost is minimized by using only talented (ordinary) labor if $r - \beta Q_t < (>)\ q$. Letting Q^* denote the level of output that satisfies $r - \beta Q_t = q$, this will be satisfied when $Q_t > (<)\ Q^*$. Hence the firm will use only talented (ordinary) labor when $Q_t > (<)\ Q^*$. Because Q and η are positively related, this also implies that there is a corresponding value η^*, that determines the choice between ordinary and talented labor. Intuitively, the value of the marginal product of talented labor is dependent on the size of the firm, as the profits to the firm from reducing its average cost are proportional to its size. Consequently, larger firms find it profitable to hire better quality employees.

Now consider the choice of output. The first-order condition for the optimal level of output is $P = \mathrm{MC}(Q_t)$, where $\mathrm{MC}(Q_t)$ reflects only labor costs and depends on whether the firm hires ordinary or talented labor. The derivation of the firm's supply curve is pictured in Figure 1. The curves $\mathrm{MC}(Q_t)_{\mathrm{L}}$ and $\mathrm{MC}(Q_t)_{\mathrm{T}}$ denote the firm's marginal cost curves using only ordinary and talented labor, respectively. It is readily established that $\mathrm{MC}(Q^*)_{\mathrm{L}} > \mathrm{MC}(Q^*)_{\mathrm{T}}$, as pictured in Figure 1. If $P \leq \mathrm{MC}(Q^*)_{\mathrm{T}}$, then $Q_t \leq Q^*$ whether the firm uses only ordinary or talented labor, and the firm maximizes its profits by using only ordinary labor. Consequently, for prices such that $P \leq \mathrm{MC}(Q^*)_{\mathrm{T}}$ the firm's supply curve is the curve $\mathrm{MC}(Q_t)_{\mathrm{L}}$. Similarly, for prices such that $P \geq \mathrm{MC}(Q^*)_{\mathrm{L}}$ the firm maximizes its profits by producing an output greater than Q^* using only talented labor, and its supply curve is the curve $\mathrm{MC}(Q_t)_{\mathrm{T}}$. Accordingly, there is a price (minus c_t) P' between $\mathrm{MC}(Q^*)_{\mathrm{T}}$ and $\mathrm{MC}(Q^*)_{\mathrm{L}}$ such that if $P < P'$ the firm uses ordinary labor and produces an output $Q_t < Q^*$ whereas if $P > P'$ the firm uses only talented labor and produces an output $Q_t > Q^*$. Consequently, for prices $P < P'$ the firm's supply curve is the curve $\mathrm{MC}(Q_t)_{\mathrm{L}}$ and for prices $P > P'$ the firm's supply curve is the curve $\mathrm{MC}(Q_t)_{\mathrm{T}}$, as pictured in Figure 1.

The model can be easily generalized to allow for multiple tasks, each requiring a distinctive type of labor. For example, suppose that the firm employs secretaries to perform clerical services, production workers to engage in manufacturing, and managers to administer the firm. The firm can hire either an ordinary or talented variant of each type of labor, with the latter paid a higher wage. Both types are equally productive at the requisite production function, but if T^i units of talented labor are hired to perform the i^{th} task, the firm's overall average cost of production will be reduced by $\beta_i T^i$ where $\beta_i > 0$ differs across tasks. For example, it might be expected that talented secretaries would have less impact on average cost than talented managers.

Following the reasoning above, for the i^{th} task there will be a critical productivity level η_i^* such that if $n_t > (<)\ \eta_i^*$ the firm will hire only talented (ordinary) labor to perform the task. For each task, the greater β_i then the lower η_i^*. Ordering tasks from lowest to highest in terms of β_i, the most productive firms with $\eta_t > \eta_i^*$ will hire talented labor to perform every task. The next most productive firms with $\eta_1^* \geq \eta_t > \eta_2^*$ will use talented labor to perform all but the first task, and so on. Since Q_t is determined by η_t, this in turn implies that the average wage paid to labor will be an increasing function of a firm's size, as reflected by its output.

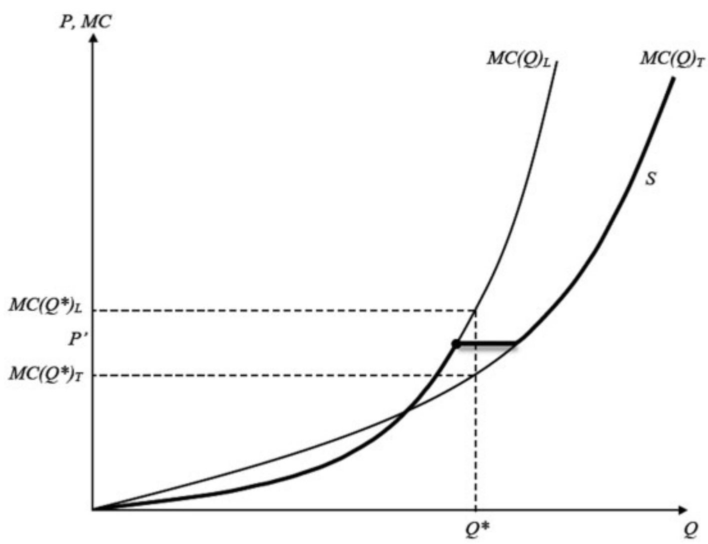

Figure 1. Derivation of the firm's supply curve

2.2 Evolution of perceived firm productivity and the set of producers

We can develop more fine-grained predictions by modeling the evolution of the firm's productivity and its perception of its productivity. Following Jovanovic (1982), we initially consider the case where firms differ regarding their productivity at the time of entry and their productivity does not change over time. Then we allow for a second productivity component in which random shocks occur that dissipate over time.

Let θ_i denote the productivity type of firm *i*. It is assumed that firms do not know their productivity type, but at the time of entry they have information about θ_i based on the pre-entry experience of their founders and the quality of the idea that prompted the formation of the firm. This is captured by assuming that firms draw their productivity type from a normal distribution with known mean $\overline{\theta}_i$ and known variance σ_θ^2, where $\overline{\theta}_i$ is larger the better the firm's pre-entry experience. Accordingly, the firm's prior distribution for θ_i at the time of entry is $N(\overline{\theta}_i, \sigma_\theta^2)$.

The firm's actual productivity in period *t*, η_{it}, is determined by $\eta_{it} = \psi(\theta_i + \varepsilon_{it})$, where ε_{it} is a temporary productivity shock that is drawn from a normal distribution with mean 0 and known variance σ_ε^2 and $\psi(.)$ is a known function such that $\psi' > 0$, $\lim_{(\theta_i+\varepsilon_{it})\to\infty}\eta_{it} = \eta_1 > 0$ and $\lim_{(\theta_i+\varepsilon_{it})\to\infty}\eta_{it} = \eta_2 < \infty$. We assume that at the beginning of each period *t* the firm chooses its output for the period, Q_{it}, based on its expected productivity at the beginning of the period and it chooses whether to hire ordinary or talented labor depending on its chosen level of output. At the end of period *t*, it can solve for its actual productivity η_{it} based on the amount of labor L_t and T_t it had to hire to produce Q_{it} according to $\eta_{it} = Q_{it}/(L_t + T_t)^\alpha$. In turn, given the known function $\psi(.)$ it can solve for $y_{it} = \theta_i + \varepsilon_{it}$.

Thus, in each period *t* the firm receives a signal y_{it}, which it can use to update its subjective distribution for θ_i according to Bayes' theorem. Let $\overline{\theta}_{it}$ and σ_{it}^2 denote the mean and variance of the firm's subjective distribution for θ_i at the beginning of period *t*, where its expected productivity equals $\psi(\overline{\theta}_{it})$. Using Bayes' theorem, the firm will update the mean of its distribution in response to a new signal y_{it} in period *t* according to:

$$\overline{\theta}_{it+1} = \overline{\theta}_{it} + (1-d)(y_{it} - \overline{\theta}_{it}), \tag{2}$$

where $d = \sigma_\varepsilon^2/(\sigma_{it}^2 + \sigma_\varepsilon^2)$. Equation (2) indicates that if $y_{it} >(<) \overline{\theta}_{it}$ the firm updates the mean of its distribution upward (downward), with the weight on the new signal greater the smaller σ_ε^2, the variance of the signal, relative to σ_{it}^2, the variance of the distribution before the new signal. It then uses the new mean to choose its output in period $t+1$ and whether to hire ordinary or talented labor. Over time σ_{it}^2 declines, hence the adjustment in the mean from each new signal declines.

Jovanovic (1982) assumes that there is an opportunity cost of production based upon alternative opportunities elsewhere and the firm knows the future stream of prices. He shows that in each period *t* there is a critical cutoff, θ_t^*, such that the firm exits if $\overline{\theta}_{it} < \theta_t^*$.[1] This result applies to our model as well. Since a firm's signals are directly related to its productivity type, $\overline{\theta}_{it}$ will be related to θ_i, the firm's true productivity, and also to $\overline{\theta}_i$, which is a function of the pre-entry experience of the firm's founders (hereafter referred to as the pre-entry experience of the firm). Thus, less efficient firms are more likely to exit, as are those with inferior pre-entry experience.

If a firm does not exit after period *t*, it adjusts its output in the next period according to whether its signal y_{it} is greater or less than $\overline{\theta}_{it}$. The larger its upward adjustment in the mean of its subjective distribution, the greater the firm's growth from period *t* to $t+1$ and thus the greater the expected increase in the wages paid to its new hires. As new signals cause less revision in $\overline{\theta}_{it}$ as firms age, growth declines with firm age and asymptotically approaches zero, causing the firm's wages to asymptotically approach a limiting value. Note that the model implies that growth in every period will be independent of $\overline{\theta}_i$. It will depend only on whether the firm's productivity type θ_i is greater or less than $\overline{\theta}_i$. Among firms that remain in the industry, over time those with $\theta_i > \overline{\theta}_i$ would be expected to grow while those with $\theta_i < \overline{\theta}_i$ would be expected to decline, in both instances at decreasing rates over time. Growth in every period will also be unrelated to the firm's size at the start of the period, which reflects its best guess of its productivity and thus size at the end of the period.

2.3 Implications

The model has a number of implications that we can test. First, the model implies that in every year, the wages of new hires are determined by the size of the firm. Therefore:

Prediction 1: In every period, the greater the size of the firm, then the greater the wages of its new hires.

1 A similar cutoff applies to the entry decision itself—a firm will only enter if $\overline{\theta}_i$ exceeds a cutoff.

We can break this down further based on the evolution of the firm's perceived productivity. Initially, the firm's output and thus hiring decisions are based entirely on $\overline{\theta}_i$, which in turn is determined by its pre-entry experience. Consequently, in its first year, the firm's wages should be based entirely on its pre-entry experience:

Prediction 2: The better the firm's pre-entry experience, then the greater the talent of the employees that it initially hires and thus the greater the wages paid to its initial hires.

After the first year, the firm will adjust its output based on the signals about its productivity, which in turn will condition its choice of labor and thus wages paid to new hires. Therefore, in each year the wages paid to new hires should be based on the firm's pre-entry experience and its past growth rates:

Prediction 3: In period t, the talent of new hires and thus the wages paid to them will be greater the better the firm's pre-entry experience and the greater its growth in all past periods.

Fourth, the model implies that hiring decisions for each type of occupation should be motivated by the same factors as overall hiring decisions:

Prediction 4: For each occupation, in each period the larger the firm's size, or alternatively the better the firm's pre-entry experience and the greater its growth in past periods, then the greater the talent and thus wages paid to its new hires.

Suppose both the firm's size and also its pre-entry experience and past growth rates are included as determinants of the wages of new hires. If pre-entry experience is measured imperfectly and size is not, then wages should be completely determined by firm size and neither proxies for the firm's pre-entry experience nor its past growth rates should influence wages:

Prediction 5: For each year, if firm size is included as a determinant of the wages of new hires, then proxies for the firm's pre-entry experience and past firm growth rates should have no effect on wages.

Last, the model has various implications about firm growth rates, most of which are spelled out in Jovanovic (1982). Over time, the least efficient firms exit. On average, these firms have less pre-entry experience (i.e., lower values of $\overline{\theta}_i$) and lower growth rates (had they not exited). Consequently, among surviving firms the mean quality of their pre-entry experience rises and the variance in the quality of their pre-entry experience falls with age. The exit of the firms that would otherwise have had lower growth rates results in a positive mean growth rate of surviving firms. Over time, the growth rates of all firms decline. Consequently, the mean and variance of the growth rate of surviving firms should decline with age. Last, in each period a firm's growth rate should be unrelated to $\overline{\theta}_i$ and hence to the quality of its pre-entry experience but is a decreasing function of its size at the start of the period. Collecting results:

Prediction 6: As firms age:

a. The mean quality of their pre-entry experience rises.
b. The variance in the quality of their pre-entry experience falls.
c. Their mean growth rate falls.
d. The variance of their growth rate falls.

3. Data and analysis

We examine the hiring behavior of new firms that entered the Danish private sector in the period 2003–2010, based on data from the period 2001–2011. The modern Danish labor market resembles the labor market in the United States in many respects. Unions set minimum wages for jobs, but firms are otherwise free to hire whomever they want and to determine how much to pay them. Employers incur low firing costs, and the annual rates of job creation and turnover are comparable to those in the United States (Sørensen and Sorenson, 2007; Dahl and Sorenson, 2010).

We exploit data on firms and employees covering the entire economy. We analyze data from government registers collected in the Integrated Database for Labor Market Research (referred to by its Danish acronym, IDA) and the Entrepreneurship Database (ED), both maintained by Statistics Denmark (hereafter, SD). IDA contains annual data on every individual residing in Denmark, including data on education, income, work experience, and occupation. The data set also links individuals to their employers. ED contains data on new limited liability firms and individually owned firms in Denmark, including their annual number of employees, industry, location, start date, exit date, and main founder. The ED was used by Dahl and Sorenson (2012, 2014).

Identification of a new firm's main founder was straightforward for non-limited liability firms due to the way that firms are registered in Denmark. For limited liability firms, SD identified the main founder based on an algorithm that uses data about the daily management of the firm, its board of directors, and its payroll. Surveys of government agencies that provide free advice to founders indicated that founders could be the managing director of the firm in the first year, the person with the highest salary in the first year, or a member of the board of directors who did not take a salary to conserve on firm liquidity. Accordingly, SD constructed the following four-step procedure to identify the main founder of limited liability firms. First, choose the person with the highest salary who was an initial employee of the firm, part of the daily management team, and on the board of directors. Second, if no one satisfied all three conditions, choose the person with the highest salary that was an initial employee of the firm and part of the daily management team. Third, if no one satisfied these two conditions, choose the first person that joined the firm who was part of the daily management team and on the board of directors. Last, if no one satisfied these conditions, choose the first person that joined the firm who was part of the daily management team. This procedure identified a founder for 97% of the limited liability firms; the other 3% were dropped from the sample.

Our sample contains 17,518 new firms founded between 2003 and 2010 that hired full-time employees.[2] For these firms, we considered the new full-time employees they hired in each year of their existence through 2011, the last year of our data. Workers are assigned to a single employer each year based on their employer as of the third week of November of that year. Thus, to be classified as a new hire in any particular year, a worker had to be employed by a firm in the third week of November of that year but not the prior year. In total, we identified 141,938 full-time employees who were hired by the 17,517 new firms in our sample through 2011. For each employee, we had data on their annual wages in the year they were hired, their occupation, annual wages in the prior year, education, age, gender, and marital status. Wages were deflated to 2005 levels using the Danish wage index for the private sector, which adjusts for the rise in wages (both nominal and real) that occurred over time.

For employers, we added a measure of their expected performance at the time of entry. We did not calculate this based on all cohorts, because the wage regressions estimated could suffer from simultaneity, because employee characteristics are influencing performance. Instead we estimated an exponential hazard model based on the performance of start-ups in the two cohorts before our period of analysis, i.e., 2001 and 2002. In this model, the hazard of exit was specified as a function of characteristics of the founder, whether the firm was constituted as a limited liability company, its industry, and its location. We included the founder's age, founder's age squared, the log of the founder's prior income, a dummy for whether the founder previously worked in the same four-digit industry as the firm he founded, and the age and size (experience) of the firm where the founder previously worked as measures of the founder's experience. All of these were expected to reduce the hazard of exit with exception of parent firm size. We included a dummy for whether the firm was constituted as a limited liability company, which we expected also to lower the hazard under the assumption that firms with better survival prospects would be more likely to benefit from limiting the liability of their owners. Last, we included 21 regional dummies to allow firm survival rates to vary by regional labor market.

The estimated coefficients of two hazard models for all but the industry and regional dummies are reported in Table 1. The first model is for all cohorts from 2001 to 2010, which enables us to compare estimated coefficients with the second model for the 2001 and 2002 cohorts. In the model for all cohorts, all are significant at the 0.01 level and all have the expected signs. In the model for the 2001 and 2002 cohorts, we find largely the same effects, expect for founder's prior income and firm age. To avoid simultaneity, we used the estimated second equation (2001–2002 cohorts) to predict the number of days of survival for each firm. We used the natural log of its predicted days of survival as our measure of $\overline{\theta}_i$.

We also computed the annual percentage change in the number of employees in the firm (measured as the difference in the log of the number of employees in consecutive years), which we used as our measure of its annual growth. In addition, we included 127 dummies for the industry of the firm and the 21 regional labor market dummies for the firm's location.

We estimated separate regressions for the employees hired in each year of a firm's existence up to 8 years. Table 2 lists the number of employers in each year and the number of employees hired each year. The 17,518 firms in our

2 This excludes the founder, who was not considered an employee.

Table 1. Exponential hazard models

Variables	Cohorts 2001–2010	Cohorts 2001–2002
Founder age	−0.103***	−0.0958***
	(0.00286)	(0.00635)
Founder age^2	0.00121***	0.00117***
	(3.66e-05)	(8.15e-05)
Unemployment history	0.185***	0.179***
	(0.00681)	(0.0145)
Ln (founder income, t − 1)	0.00461***	0.00194
	(0.000957)	(0.00203)
Spin-off (same four-digit industry)	−0.244***	−0.321***
	(0.00909)	(0.0199)
Limited liability form	−0.564***	−0.542***
	(0.00943)	(0.0211)
Parent firm age	0.00342***	0.000153
	(0.000309)	(0.000636)
Parent firm size	1.65e-05***	6.02e-06
	(1.80e-06)	(3.75e-06)
Constant	−12.60***	−6.482***
	(0.643)	(1.320)
Observations	538,874	134,054
Number of firms	134,443	24,348
Log-likelihood	−174,522	−35,257

Standard errors in parentheses
Significance levels: ***$P < 0.01$.

Table 2. Number of observations

Firm age/year	Average firm size	Minimum firm size	Maximum firm size	Number of firms hiring	Number of new hires	Entry cohorts
Firm age 0/year 1	2.27	1	775	17,518	37,376	2003–2010
Firm age 1/year 2	4.12	1	788	14,766	33,337	2003–2009
Firm age 2/year 3	5.15	1	725	10,807	23,738	2003–2008
Firm age 3/year 4	6.05	1	741	8006	18,298	2003–2007
Firm age 4/year 5	6.49	1	623	5605	13,118	2003–2006
Firm age 5/year 6	7.38	1	613	3589	8848	2003–2005
Firm age 6/year 7	7.35	1	633	2036	4792	2003–2004
Firm age 7/year 8	7.65	1	110	958	2431	2003

data set hired a total of 37,376 employees in their first year, which constitutes our sample for year 1. In year 2, 14,766 firms (the rest exited after year 1 or did not hire additional employees) hired a total of 33,337 employees, which constitutes our sample for year 2. The number of firms declines in subsequent years due to exit, a decline in hiring, and the loss of the later entrants from the sample. Table 2 also reports the mean number of employees of firms (full-time equivalents) at each age. On average, the firms were quite small. In their first year, they had an average of 2.27 employees, which increased to 7.65 in year 8 for those firms (in the 2003 entry cohort) that survived that long. The largest firm in our data set across all years had 788 employees.

In each regression, the dependent variable was the natural log of the (deflated) wages of the new employee[3] and the independent variables included the natural log of the predicted years of survival of the employer and the growth

3 We also estimated regressions with the log of the employee's total income as the dependent variable, and our findings were similar.

rate in the number of employees at the employer in the current and past years. We also included five dummies for the employee's occupation: Top managers, managers, white-collar, blue-collar, and unskilled, with unskilled as the omitted category. The industry and regional dummies were also included. We estimated a first set of regressions in which we did not include any controls for characteristics about the employees potentially correlated with their talent. These regressions reflect the total influence of initial firm survival prospects and subsequent growth on the quality of employees hired, as reflected in their wages. We also estimated a second set of regressions in which we included controls for the characteristics of the employees, including their natural log of the months of education, natural log of the prior wage, age, age squared, gender, and marital status.[4] In the interest of saving space, we did not report the coefficient estimates of these controls. These are, however, available upon request. Robust standard errors were computed by clustering the observations for each firm.

Table 3 reports the coefficient estimates for 24 regressions corresponding to the hires in the initial year and years 2 through 8 without any controls for characteristics of the employees. The table is divided into three panels with eight regressions in each panel (one for each year). We test the first theoretical prediction in the top panel with regressions only including log size (full-time equivalents) as a predictor. Estimates of log size are positive and significant in the years 1 through 8, confirming that the greater the size of the firm, the greater the wages of its new hires.

The only firm measure in the first regression of the middle panel is the log of the predicted survival (LPS). Consistent with the second prediction of the theory, the coefficient estimate for LPS is positive and significant. It implies that for each 1% increase in the predicted survival, the wages of employees increase by approximately 0.4%. Thus, if the predicted survival doubled from its mean of 2784 days (see Table 7) to 5568 days, wages would rise by approximately 38%.

For year 2, we add the growth rate of the number of employees of (surviving) firms from year 1 to year 2 as a regressor. The coefficient estimate of LPS is again positive and significant. The coefficient estimate of the growth rate is also positive and significant. It implies that if the number of employees doubled, then wages would rise by 15.5%. Both coefficient estimates are consistent with the second prediction of the theory. For years 3 through 8, we add lagged annual growth rates as regressors. The coefficient estimates of LPS remain significant in all years. They vary in magnitude but are generally smaller than the coefficient estimate of LPS in year 1. The coefficient estimates for the most recent growth rate are significant and positive in all years. These estimates are generally larger than for the growth rate in year 2, but offsetting this is that firm growth declines with age (see Table 7). There are 21 lagged growth rates in the regressions for years 3 through 8. The coefficient estimates for 16 of them are significant, with 15 positive.

We add log size to the regressions with LPS and the growth rates and present these in the bottom panel of Table 3. Given that size is a better indicator of the firm's productivity, we would expect that the effects of LPS and the growth rates disappear with the introduction of size. This is not the case. The estimates are generally lower than without size, but there are still significant effects of LPS and growth rates on wage of new hires.

Thus, overall the estimates provide support for the second and third predictions of the theory. No doubt, LPS and the firm growth rates are measured with error, which would be expected to bias their coefficient estimates toward zero. Nonetheless, many of the coefficient estimates are significant and nearly all of these are positive and substantial. It appears that new firms with greater initial survival prospects and that experienced greater growth over time consistently paid higher wages to their hires.

The second set of estimates, which includes controls for employee characteristics, is reported in Table 4. The two key measures of employee talent are the natural log of the employee's prior wage and the employee's education, which is represented by the natural log to the months of education. Also included are the employee's age, age squared, gender, and marital status as proxies for talent. In the interest of space, we only present the estimates of prior wage. With controls for the quality of employees, it was expected that the coefficient estimates of LPS and the growth rates would decline.

The coefficient estimates for the log of the employee's prior wage are all positive and significant. They are in the range of 0.15 and 0.19, which implies a 0.15%–0.19% increase in current wages for each 1% rise in prior wages. Older employees, males, longer educated, and married individuals earn greater wages, with age having a diminishing

4 We also estimated both sets of regressions including year dummies, but this had little effect on our estimates, as would be expected, given that wages are deflated.

Table 3. Regression of log of wage paid to new full-time hires in years 1–8

Hires	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Ln (size)	0.265***	0.169***	0.134***	0.107***	0.146***	0.137***	0.115***	0.143***
	(0.0133)	(0.00943)	(0.0103)	(0.0120)	(0.0120)	(0.0144)	(0.0209)	(0.0383)
R^2	0.169	0.113	0.130	0.121	0.141	0.144	0.149	0.178
Ln (predicted survival)	0.380***	0.292***	0.278***	0.209***	0.250***	0.236***	0.222***	0.178**
	(0.0208)	(0.0210)	(0.0250)	(0.0279)	(0.0320)	(0.0391)	(0.0578)	(0.0810)
Growth year 1–2		0.224***	0.0557***	0.0341	0.0587**	0.0786***	0.0735*	0.0535
		(0.0158)	(0.0157)	(0.0234)	(0.0264)	(0.0265)	(0.0405)	(0.0566)
Growth year 2–3			0.268***	0.0670**	0.0951***	0.125***	0.0843	0.193**
			(0.0247)	(0.0291)	(0.0310)	(0.0408)	(0.0614)	(0.0961)
Growth year 3–4				0.281***	0.0648*	0.190***	0.151**	0.168*
				(0.0321)	(0.0370)	(0.0470)	(0.0655)	(0.0992)
Growth year 4–5					0.325***	0.0840**	0.0996	−0.351**
					(0.0336)	(0.0415)	(0.0759)	(0.149)
Growth year 5–6						0.382***	−0.0413	0.245**
						(0.0603)	(0.0716)	(0.123)
Growth year 6–7							0.384***	0.195*
							(0.0764)	(0.0995)
Growth year 7–8								0.278*
								(0.169)
R^2	0.129	0.118	0.136	0.125	0.144	0.150	0.156	0.189
Ln (size)	0.245***	0.0964***	0.0868***	0.0839***	0.110***	0.0828***	0.0668**	0.127***
	(0.0137)	(0.0135)	(0.0130)	(0.0171)	(0.0166)	(0.0184)	(0.0282)	(0.0487)
Ln (predicted survival)	0.173***	0.203***	0.190***	0.118***	0.143***	0.155***	0.159**	0.0418
	(0.0211)	(0.0237)	(0.0281)	(0.0301)	(0.0351)	(0.0430)	(0.0629)	(0.101)
Growth year 1–2		0.157***	−0.0119	−0.0184	−0.0142	0.0224	0.0248	−0.0253
		(0.0186)	(0.0192)	(0.0262)	(0.0294)	(0.0294)	(0.0452)	(0.0659)
Growth year 2–3			0.208***	0.0117	0.0211	0.0730*	0.0415	0.116
			(0.0285)	(0.0334)	(0.0340)	(0.0426)	(0.0648)	(0.0954)
Growth year 3–4				0.235***	−0.0220	0.123**	0.0941	0.0507
				(0.0339)	(0.0402)	(0.0487)	(0.0736)	(0.113)
Growth year 4–5					0.241***	0.0171	0.0477	−0.415***
					(0.0343)	(0.0433)	(0.0808)	(0.151)
Growth year 5–6						0.332***	−0.0908	0.127
						(0.0613)	(0.0779)	(0.131)
Growth year 6–7							0.334***	0.109
							(0.0811)	(0.100)
Growth year 7–8								0.171
								(0.173)
R^2	0.172	0.124	0.140	0.130	0.150	0.153	0.158	0.192
Observations	37,376	33,337	23,554	18,073	12,921	8721	4723	2374

Robust standard errors in parentheses, clusted at the level of the firm. All regressions include controls for industries (127), local labor markets (21), and occupational levels (5).

Significance levels: $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

effect on wages, as is commonly found. The addition of the employee characteristics greatly increases the explanatory power of the regressions, with the R^2 rising from around 0.15 to 0.25 in the various regressions.

Again, we look first at the effect of size on wages of new hires in the top panel of Table 4. The effect of size is slightly lower with the introduction of employee characteristics. Comparing the coefficient estimates for LPS and the growth rates in Table 4 (middle panel) to those in Table 3 (middle panel), the estimates in Table 4 are generally smaller than those in Table 3, as expected. This reflects that both LPS and the growth rates tend to be positively correlated with the educational level of employees and their past wage (controlling for their educational level), which

Table 4. Regression of log of wage paid to new full-time hires in years 1-8 with individual characteristics as controls

Hires	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Ln (size)	0.271***	0.174***	0.133***	0.115***	0.148***	0.122***	0.0829***	0.150***
	(0.0143)	(0.00952)	(0.0110)	(0.0125)	(0.0126)	(0.0169)	(0.0241)	(0.0338)
Ln (wage, t–1)	0.185***	0.147***	0.152***	0.137***	0.131***	0.129***	0.0422*	0.0793**
	(0.0111)	(0.0106)	(0.0159)	(0.0134)	(0.0149)	(0.0199)	(0.0242)	(0.0371)
R^2	0.255	0.185	0.193	0.179	0.188	0.201	0.229	0.260
Ln (predicted	0.294***	0.230***	0.221***	0.179***	0.218***	0.205***	0.222***	0.249**
survival)	(0.0257)	(0.0240)	(0.0290)	(0.0324)	(0.0360)	(0.0474)	(0.0742)	(0.103)
Growth year 1–2		0.227***	0.0578***	0.0448*	0.0497*	0.0690**	0.0277	0.0959*
		(0.0152)	(0.0168)	(0.0256)	(0.0292)	(0.0296)	(0.0405)	(0.0563)
Growth year 2–3			0.253***	0.0721***	0.0949***	0.117***	0.133**	−0.0420
			(0.0226)	(0.0254)	(0.0319)	(0.0434)	(0.0657)	(0.0826)
Growth year 3–4				0.290***	0.123***	0.222***	0.114	0.168
				(0.0299)	(0.0394)	(0.0495)	(0.0725)	(0.104)
Growth year 4–5					0.291***	0.130**	0.0523	−0.136
					(0.0339)	(0.0513)	(0.0897)	(0.126)
Growth year 5–6						0.369***	−0.0675	0.254*
						(0.0607)	(0.0834)	(0.154)
Growth year 6–7							0.362***	0.0287
							(0.0814)	(0.129)
Growth year 7–8								0.463***
								(0.119)
Ln (Wage, t–1)	0.177***	0.141***	0.149***	0.136***	0.134***	0.124***	0.0482**	0.0837**
	(0.0114)	(0.0103)	(0.0159)	(0.0137)	(0.0150)	(0.0197)	(0.0245)	(0.0374)
R^2	0.198	0.185	0.196	0.182	0.189	0.211	0.243	0.272
Ln (Size)	0.265***	0.111***	0.0986***	0.0992***	0.118***	0.0609***	0.0425	0.137**
	(0.0145)	(0.0122)	(0.0145)	(0.0170)	(0.0174)	(0.0205)	(0.0345)	(0.0592)
Ln (predicted	0.0622**	0.130***	0.122***	0.0670*	0.100***	0.147***	0.184**	0.109
survival)	(0.0243)	(0.0262)	(0.0323)	(0.0360)	(0.0386)	(0.0519)	(0.0783)	(0.126)
Growth year 1–2		0.151***	−0.0176	−0.0132	−0.0252	0.0309	−0.00416	0.0152
		(0.0175)	(0.0206)	(0.0279)	(0.0325)	(0.0316)	(0.0496)	(0.0615)
Growth year 2–3			0.185***	0.00784	0.0210	0.0797*	0.107	−0.124
			(0.0273)	(0.0313)	(0.0351)	(0.0448)	(0.0700)	(0.0883)
Growth year 3–4				0.242***	0.0330	0.175***	0.0759	0.0414
				(0.0315)	(0.0423)	(0.0517)	(0.0820)	(0.120)
Growth year 4–5					0.204***	0.0819	0.0179	−0.207*
					(0.0349)	(0.0538)	(0.0949)	(0.125)
Growth year 5–6						0.336***	−0.0983	0.118
						(0.0613)	(0.0911)	(0.168)
Growth year 6–7							0.331***	−0.0651
							(0.0884)	(0.136)
Growth year 7–8								0.347***
								(0.126)
Ln (Wage, t–1)	0.183***	0.144***	0.149***	0.134***	0.133***	0.124***	0.0478*	0.0800**
	(0.0111)	(0.0104)	(0.0158)	(0.0135)	(0.0150)	(0.0197)	(0.0244)	(0.0373)
R^2	0.256	0.194	0.202	0.190	0.198	0.213	0.244	0.277
Observations	23,410	19,262	13,878	10,728	7659	5206	2672	1257

Robust standard errors in parentheses, clusted at the level of the firm. All regressions include controls for age, age^2, gender, married, months of education (ln), industries (127), local labor markets (21), and occupational levels (5).

Significance levels: ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

was confirmed from (unreported) regressions of each variable on LPS and the growth rates. At the same time, the increase in the explanatory power of the regressions lowers the standard errors of the coefficient estimates and many remain significant. The coefficient estimate of LPS is significant in all of the eight regressions, and all are positive. The coefficient estimate of the most recent growth rate is significant and positive in all regressions. Among the 21 lagged growth rates, 13 are significant, with all 13 positive. These effects are lower with the introduction of size as shown in the bottom panel. There is still a component to be explained by LPS and growth rates, even with the introduction of a better indicator of productivity. Thus, even controlling for the education and past wages of the employees, the wages of employees were still greater in firms with better initial survival prospects and higher growth rates.

The estimates suggest that the wages of employees changed substantially when they moved to new firms, as the coefficient of log prior wages is well below one. However, the coefficient of log wages will be biased toward zero if wages contain a substantial transitory component, which would not be predictive of the next year's wage. To test this, we used the prior year's wage (i.e., wages 2 years before being hired at a new firm) as an instrument for the lagged wage. The estimates for these regressions are reported in Table 5. The coefficient estimates for the lagged wage are now considerably higher, rising to about 0.5, consistent with wages containing a substantial transitory component. The coefficient estimates of LPS and the growth rates are somewhat smaller than in Table 4, as would be expected, and as a consequence less of them are significant. But overall the patterns are similar to those in Table 4.

The theory predicts that better firms hire more talented workers for all types of occupations. Our data classify workers into five occupations, with most of the workers in the bottom occupations. This made it difficult to estimate with any precision regressions for workers in the top two occupational groups, even for the first couple of years when we had the most observations. Instead, we estimated a single regression for the log of wages of the employees hired in year 1 and year 2 in which LPS was allowed to have a different effect for each occupation by entering LPS alone and interacted with the four higher occupations. We estimated this regression for the first year, without and with controls for the employee characteristics. The coefficient estimates for these regressions are reported in Table 6. None of the interaction effects are significant in the first year, but for the second-year hires, we find a positive additional effect of LPS on wages of managers.[5]

The last set of predictions of the theory pertains to firm growth rates. Table 7 reports the mean and variance of the annual growth rates, the mean and variance of LPS, and the coefficient estimates of a regression with LPS and log size as predictors of growth rates. As predicted, the mean firm growth rate declines with age, consistent with Jovanovic's model. The variance of the firm growth rates also declines with age, consistent with prediction 4 of the theory.

The mean of LPS is stable over time, but the variance of LPS initially falls modestly with age, as predicted. Last, the estimates of LPS on growth are significant and the estimates of size on growth are significant and negative. This is consistent with the prediction of the theory and shows that the firm's growth rate is weakly related to the quality of its pre-entry experiences but is a decreasing function of its size at the start of the period.

4. Discussion

Lucas (1978) proposed a theory in which individuals differ regarding their ability to manage others. Those with the greatest ability become entrepreneurs and the others become workers. Among the entrepreneurs, the greater their ability, then the larger the number of workers they hire and the greater their profits.

We took this perspective one step further. Similar to the entrepreneurs, we allowed workers to have different abilities. Larger firms were modeled as earning a greater return from hiring more able workers. Consequently, better firms were predicted to hire better workers. We assumed that firms initially had a sense of their ability based upon the experience of their founders, and hence firms with more experienced founders would hire better quality workers from their outset. We also assumed that with experience firms would gain a better sense of their abilities, which would also influence the quality of their subsequent hires.

5 We also estimated separate regressions for limited and non-limited liability firms to check that it was not merely this distinction that was driving the estimated effects of LPS and the growth rates in the various regressions. The coefficient estimates for each of the groups for the various regressions were not markedly different and were similar to those in Table 4, suggesting that the same forces shaped the hiring decisions of both types of firms.

Table 5. Regression of log of wage paid to new full-time hires in years 1–8 with log of wage (t–2) as instrument for log of wage (t–1)

Hires	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Ln (size)	0.273***	0.179***	0.134***	0.109***	0.139***	0.102***	0.0866***	0.124***
	(0.0151)	(0.0106)	(0.0112)	(0.0123)	(0.0136)	(0.0182)	(0.0263)	(0.0354)
Ln (wage, t–1)	0.528***	0.565***	0.398***	0.427***	0.428***	0.540***	0.488***	0.225
	(0.0362)	(0.0339)	(0.0390)	(0.0457)	(0.0485)	(0.0785)	(0.103)	(0.156)
R^2	0.170	0.054	0.154	0.115	0.128	0.087	0.131	0.238
Ln (predicted survival)	0.248***	0.198***	0.207***	0.148***	0.178***	0.144***	0.180**	0.254**
	(0.0296)	(0.0272)	(0.0318)	(0.0351)	(0.0392)	(0.0521)	(0.0806)	(0.107)
Growth year 1–2		0.231***	0.0535***	0.0438*	0.0537*	0.0791**	0.0286	0.135**
		(0.0170)	(0.0173)	(0.0256)	(0.0306)	(0.0316)	(0.0447)	(0.0553)
Growth year 2–3			0.246***	0.0578**	0.0728**	0.0893*	0.104*	−0.105
			(0.0231)	(0.0260)	(0.0350)	(0.0456)	(0.0626)	(0.0852)
Growth year 3–4				0.265***	0.129***	0.199***	0.0984	0.157
				(0.0296)	(0.0398)	(0.0515)	(0.0799)	(0.107)
Growth year 4–5					0.260***	0.113**	0.0564	−0.0832
					(0.0336)	(0.0514)	(0.0887)	(0.127)
Growth year 5–6						0.321***	−0.0326	0.218
						(0.0652)	(0.0862)	(0.160)
Growth year 6–7							0.362***	0.0199
							(0.0810)	(0.129)
Growth year 7–8								0.588***
								(0.120)
Ln (Wage, t–1)	0.494***	0.544***	0.382***	0.411***	0.424***	0.524***	0.486***	0.198
	(0.0363)	(0.0334)	(0.0396)	(0.0459)	(0.0494)	(0.0774)	(0.103)	(0.148)
R^2	0.121	0.065	0.160	0.122	0.130	0.103	0.147	0.268
Ln (size)	0.273***	0.120***	0.105***	0.0996***	0.115***	0.0495**	0.0589	0.0593
	(0.0155)	(0.0135)	(0.0145)	(0.0162)	(0.0185)	(0.0227)	(0.0378)	(0.0577)
Ln (predicted survival)	0.00174	0.0911***	0.102***	0.0341	0.0617	0.0966*	0.127	0.191
	(0.0282)	(0.0292)	(0.0345)	(0.0388)	(0.0417)	(0.0573)	(0.0858)	(0.130)
Growth year 1–2		0.149***	−0.0257	−0.0125	−0.0193	0.0486	−0.0139	0.101*
		(0.0195)	(0.0208)	(0.0276)	(0.0342)	(0.0338)	(0.0567)	(0.0587)
Growth year 2–3			0.175***	−0.00662	−0.00136	0.0592	0.0680	−0.141
			(0.0278)	(0.0316)	(0.0382)	(0.0478)	(0.0680)	(0.0926)
Growth year 3–4				0.220***	0.0421	0.162***	0.0455	0.105
				(0.0308)	(0.0431)	(0.0538)	(0.0885)	(0.119)
Growth year 4–5					0.176***	0.0747	0.00717	−0.113
					(0.0349)	(0.0544)	(0.0952)	(0.126)
Growth year 5–6						0.296***	−0.0745	0.156
						(0.0653)	(0.0935)	(0.177)
Growth year 6–7							0.317***	−0.0226
							(0.0893)	(0.141)
Growth year 7–8								0.535***
								(0.126)
Ln (Wage, t–1)	0.528***	0.552***	0.391***	0.414***	0.426***	0.523***	0.486***	0.195
	(0.0367)	(0.0335)	(0.0395)	(0.0459)	(0.0489)	(0.0771)	(0.103)	(0.149)
R^2	0.170	0.071	0.165	0.129	0.137	0.105	0.149	0.269
Observations	19,199	15,563	11,338	8846	6442	4373	2253	1066

Robust standard errors in parentheses, clusted at the level of the firm. All regressions include controls for age, age^2, gender, married, months of education (ln), industries (127), local labor markets (21), and occupational levels (5).

Significance levels: $***P<0.01$, $**P<0.05$, $*P<0.1$.

Table 6. Interaction effects on log of wage paid to first 2-year hires, with and without individual characteristics as controls

HIres	Year 1	Year 1	Year 2	Year 2
Ln (predicted survival)	0.365***	0.338***	0.336***	0.315***
	(0.0240)	(0.0230)	(0.0251)	(0.0247)
Blue collar	−0.222	−0.0210	0.0252	0.130
	(0.182)	(0.161)	(0.197)	(0.191)
White collar	−0.172	−0.131	0.305	0.319
	(0.556)	(0.549)	(0.358)	(0.344)
Managers	−0.0441	−0.0629	−1.412**	−1.265**
	(0.380)	(0.379)	(0.602)	(0.569)
Top managers	1.416	1.328	1.348	1.142
	(0.861)	(0.843)	(0.975)	(1.001)
LPS x Blue collar	0.0242	0.00395	−0.00718	−0.0161
	(0.0226)	(0.0200)	(0.0245)	(0.0237)
LPS x White collar	0.0429	0.0309	−0.0183	−0.0262
	(0.0696)	(0.0687)	(0.0446)	(0.0428)
LPS x Managers	0.0375	0.0284	0.203***	0.173**
	(0.0473)	(0.0471)	(0.0756)	(0.0714)
LPS x Top managers	−0.115	−0.121	−0.104	−0.0970
	(0.107)	(0.105)	(0.121)	(0.125)
Employee characteristics	No	Yes	No	Yes
Observations	37,263	36,540	33,178	32,419
R^2	0.126	0.172	0.095	0.142

Robust standard errors in parentheses, clusted at the level of the firm. All regressions include controls for industries (127), local labor markets (21), and occupational levels (5).

Significance levels: $^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$.

Table 7. Mean and variance of predicted survival and growth

Year	Growth		Ln (predicted survival)		Regression with growth as the dependent variable	
	Mean	Variance	Mean	Variance	LPS est	Ln (size) est
Year 1	–	–	7.932	0.270	–	–
Year 2	0.464	0.172	7.926	0.308	0.020***	−0.231***
Year 3	0.189	0.097	7.925	0.269	−0.058***	−0.174***
Year 4	0.138	0.084	7.927	0.260	−0.051***	−0.117***
Year 5	0.107	0.081	7.934	0.238	−0.053***	−0.105***
Year 6	0.067	0.066	7.931	0.217	−0.047***	−0.085***
Year 7	0.020	0.066	7.950	0.224	−0.056***	−0.077***
Year 8	0.052	0.057	7.957	0.218	−0.037***	−0.063***

Significance levels: $^{***}P<0.01$.

We argued that the prospects of firms, in terms of their longevity, were related to the pre-entry experience of their founders. Similar to the findings for Danish spinoff entrants (Dahl and Reichstein, 2007; Dahl and Sorenson, 2012), firms founded by individuals who previously worked for an employer in the same industry survived longer in our analysis. Founders who worked for longer-lived firms also survived longer, which is consistent with the findings for historical entrants in a large number of industries studied in the literature, e.g., the automobiles (Klepper, 2007), tires (Buenstorf and Klepper, 2010), hard disk drives (Agarwal *et al.*, 2004), and law firms (Phillips, 2002). Founders who had greater earnings also survived longer, which is consistent with Gordon Moore's presumption that his past success with Fairchild augured well for Intel's prospects. Last, new firms that incorporated also survived longer. Together,

Table 8. Average log wage for exiting and continuing firms, for each cohort

Cohort	2003		2004		2005		2006		2007		2008		2009		2010	
Year	Continue	Exit	Continue	Exit	Continue	Exit	Continue	Exit	Continue	Exit	Continue	Exit	Continue	Exit	Continue	Exit
Year 1	11.039	10.646	11.056	10.792	11.156	10.804	11.219	11.001	11.346	10.983	10.963	10.550	10.950	10.493	10.952	10.599
Year 2	11.401	11.053	11.506	10.958	11.576	11.194	11.663	11.252	11.293	10.802	11.230	10.646	11.291	10.716	11.290	10.390
Year 3	11.575	11.144	11.640	11.291	11.734	11.354	11.341	10.792	11.304	10.765	11.348	10.716	11.325	10.741		
Year 4	11.700	11.327	11.788	11.422	11.399	10.816	11.352	10.742	11.406	10.862	11.377	10.717				
Year 5	11.854	11.303	11.476	10.859	11.397	10.755	11.429	10.699	11.400	10.678						
Year 6	11.490	10.980	11.485	10.948	11.460	10.812	11.471	10.699								
Year 7	11.502	10.934	11.511	10.968	11.458	10.756										
Year 8	11.564	10.961	11.522	10.558												
Year 9	11.583	10.930														

all of these factors had a substantial effect on the quality of the initial hires of new firms in all occupations, as reflected in their earnings. They were related to the earnings of subsequent hires as well.

Based on Jovanovic's (1982) model of firm selection, we expected that firm growth rates would reflect adjustments in a firm's perception of its ability, which would in turn influence the quality of its subsequent hires given its initial performance prospects. Consistent with these predictions, a firm's most recent growth experience generally had a sizable influence on the earnings of its new hires. Its past growth rates also influenced the earnings of its hires, although with less consistency than its recent growth rate.

As would be expected, as we introduced more controls for the quality of workers, the effects of firms' initial survival prospects and subsequent growth on the earnings of their hires declined, but did not go away entirely. On average, individuals improved their earnings when they moved to new firms, and this was especially so when they were hired by firms with better initial survival prospects and that grew by greater rates over time. This may reflect a further sorting of better workers to better firms based on factors not measured in our registry data.

The extent to which firms differed in the wages paid to their employees based on their performance can be gauged by comparing the average log wages of the employees of exiting and continuing producers. In Table 8, for each cohort of entrants the average log wages of exiters and continuers are reported annually. Differences tend to be pronounced, particularly in the first few years of an entry cohort when the heterogeneity among producers is greatest. For example, in year 1 the average log wages of the entrants in the 2003 cohort that exited after 2003 is 0.393 lower than those that continued producing after the first year, which translates into a percentage difference of 48%. In all the entry cohorts, there is a marked difference in all years between the log wages of exiting and continuing producers.

It has long been known that within industries, workers earn higher wages in larger plants and firms (Oi and Idson, 1999). Much of this has to do with larger firms hiring higher quality workers (Abowd, Kramarz, and Margolis, 1999), and many theories have been proposed to explain why this is so. Each of these theories also provides a potential alternative explanation for our findings. Some of them can be ruled out given the nature of our sample. For example, it has been conjectured that larger firms have more difficulty monitoring their workers than smaller firms and may hire better quality workers to economize on monitoring costs. But our firms are so small at the outset that differential monitoring costs could not have played much, if any, role in accounting for their different hiring choices. Some theories conjecture that it is not size but age that influences hiring decisions, with size and age positively correlated. But this too cannot explain our findings since they hold for comparably aged firms. Some theories appeal to the greater market power of larger firms as the basis for them paying higher wages, but our firms are much too small, particularly at their outset, for this to be relevant.

Other theories feature how large size can provide cheaper access to capital (and other inputs), confer greater returns from adopting advanced technologies, or enhance the return from investments in worker training, all of which can provide a rationale for larger firms to hire better quality workers. Again, it would seem that the firms in our sample are too small for these factors to be relevant, particularly regarding their initial hires. But it is possible that firms with better founders may be more able to exploit technologies that require better quality workers. This could explain our findings if the type of technology employed by firms at any given moment is related to their LPS and current and past growth rates.

Table 9. Regressions of logged capital to labor ratio (total assets per employee) in years 1–8

Hires	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
Ln (predicted survival)	0.475***	0.280***	0.263***	0.315***	0.379***	0.361***	0.430***	0.373***
	(0.0163)	(0.0155)	(0.0177)	(0.0198)	(0.0233)	(0.0282)	(0.0353)	(0.0454)
Growth year 1–2		0.0740***	−0.00874	−0.0242	0.00309	0.00550	0.0110	0.0401
		(0.0136)	(0.0160)	(0.0183)	(0.0204)	(0.0241)	(0.0307)	(0.0392)
Growth year 2–3			−0.0866***	−0.0548**	0.0155	0.0721*	0.108**	0.0765
			(0.0211)	(0.0266)	(0.0315)	(0.0374)	(0.0470)	(0.0619)
Growth year 3–4				−0.129***	0.0176	0.0312	0.0651	0.0569
				(0.0254)	(0.0321)	(0.0393)	(0.0482)	(0.0582)
Growth year 4–5					−0.0820***	0.0413	0.153***	0.0499
					(0.0297)	(0.0387)	(0.0506)	(0.0706)
Growth year 5–6						−0.148***	−0.0286	0.137**
						(0.0346)	(0.0488)	(0.0685)
Growth year 6–7							−0.167***	−0.0200
							(0.0442)	(0.0677)
Growth year 7–8								−0.0918
								(0.0662)
Observations	26,164	31,024	25,557	20,797	15,834	11,448	7387	4360
R^2	0.262	0.253	0.243	0.253	0.259	0.255	0.288	0.297

Significance levels: $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

We test this by using a firm's capital-labor ratio, measured by its total assets per employee, as proxy for the type of technology it employs. We estimate a separate regression for each year, analogous to the regressions in Table 3. In each regression, the dependent variable is the firm's assets per employee in that year and the independent variables are the firm's LPS, its current and past growth rates, and the industry and regional dummies. We expect the coefficients for LPS and the growth rates to be positive if their influence on hiring choices operates through the technology adopted by firms.

The coefficient estimates for these regressions are presented in Table 9. In year 1, the coefficient of LPS is positive and significant, indicating that firms with better survival prospects (based on the quality of its founder, among other factors) did exploit more capital-intensive technologies. Over time, the coefficient estimate of LPS remains positive and significant, while the coefficient estimates of the current and past growth rates are all negative and significant (except from Year 2). While this is not what would be expected if a firm's hiring decisions were based on the capital intensity of its technology, it is possible that firms do not adjust their capital continuously but with a lag. If so, then in the later regressions the coefficient estimates of the early growth rates would be expected to be positive, while they are in fact negative.

A theory with greater promise to explain our findings is Kremer's (1993) O-Ring theory. It posits that the productivity of workers is interdependent, which implies that workers will be sorted into firms according to their ability. Thus, similar to our theory, it implies that better workers will work together. However, the O-Ring theory does not make any predictions about which types of firms will hire better quality workers. It assumes all firms are alike and will earn zero economic profits, hence will be indifferent between hiring high- or low-quality workers. But if firms are allowed to differ based on the quality of their founders, the logic of the theory suggests that better firms would hire better workers. The mechanism for this sorting is similar to our model in that better workers are more valuable to better firms. In our theory, though, the value of a more productive worker is based only on the size of the firm whereas in the O-Ring theory it is based on the productivity of the other workers in the firm.

Clearly, it will not be easy to distinguish the O-Ring theory from our model, nor to assess the extent to which the hiring choices of better firms are motivated by the use of different technologies versus their mere size. Regardless of the precise conduit by which the quality of a firm conditions hiring choices, all of these theories suggest that initial differences in new firms based on their founders will get amplified as firms age. Firms with better founders will hire better workers because they can best profit from such a strategy, and they will grow to be larger and survive longer than other firms. The match between the quality of a firm's workers and its size (in our model), technology employed, or overall work force quality (in the O-Ring theory) can provide a lasting advantage that outlives the firm's founder if the firm's output, technology, and/or the quality of its workers cannot be easily adjusted. This can help explain why in a number of industries the characteristics of firms at the time of entry appear to have had very long-lived effects on their hazard of exit (Carroll *et al*., 1996; Klepper and Simons, 2000; Klepper, 2002; Thompson, 2005; Dahl and Sorenson, 2014). Even if those characteristics do not persist, if they enable the firm to grow large initially and hire better quality workers, the advantage of the firm will endure.

The limitation of our empirical analysis is that it does not provide causal inference regarding the exact mechanism. As discussed at length above, we frame our formal model based on the argument that strong founders hire better workers that lead to better performance. Empirically, we show associations between the initial survival prospects, growth signals, and the quality of employees in terms of their wage levels. The proposed mechanism derived from the model and empirical results can also be seen as matching mechanism of complementary skills between entrepreneurs and employees, where skilled entrepreneurs are better able to hire skilled employees, emphasizing a two-sided labor market matching process where employees also decide to work for entrepreneurs, because of the complementarities of skills and not necessarily due to the choices of entrepreneurs. Again, this follows the arguments of the O-Ring theory (Kremer, 1993). In our case, the empirical design does not enable us to disentangle the different explanations, but further research will hopefully show how and why the matching of employees to entrepreneurs enhance the performance of new ventures.

5. Conclusion

We developed a simple model of the hiring decisions of new firms. The model generated a number of predictions that guided our analysis of the hiring choices of new Danish firms. Our findings strongly point to the influence of founders on firm hiring choices, whether it be through the size of the firm, the productivity of workers, or the method of production. Our findings also suggest that firms have some knowledge of their competitive prospects from the outset and gain a better sense of their prospects over time, which in turn influences their hiring choices.

Our theory provides a rationale for how initial differences in new firms related to their founders can get amplified through their hiring decisions, which can give rise to an enduring firm capability. Kremer (1993) uses a similar notion to explain differences across developed and developing economies in terms of the organization and performance of their firms. More broadly, Murphy *et al*. (1991) contend that the ability of an economy to allocate its best talent to productive careers is a key determinant of its performance. Surely one element of this ability is the extent to which better workers are matched to better entrepreneurs. Thus, the study of the hiring practices of new firms promises to illuminate a set of important issues related to growth and development.

We have just scratched the surface of the hiring practices of new firms. The flip side of hiring is retention, which can also be studied for new firms. It would also be useful to compare the hiring practices of new firms with those of old firms in the same industry to understand how new firms compete with larger rivals. Regions could also be compared in terms of firm hiring practices to assess how the size of the labor market conditions the allocation of workers to new firms. Our findings suggest a systematic process is at work in the matching of employees to founders of new firms, and further investigation of this process may provide significant insights into the performance and strategies of firms.

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