Mobilizing Social Capital Through Employee Spinoffs: Evidence from Brazil*

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Abstract

Many founding teams of new firms form at a common employer. We model team formation and the entry of employee spinoffs by extending the Jovanovic (1979) theory of job matching and employer learning. In our social-capital model employees learn about their colleagues' qualities at an even faster rate than the employer and recruit suitable colleagues to join the spinoff firm. For spinoff firms, our model predicts that the separation hazard is lower among founding team members than among workers hired from outside at founding, and that this difference shrinks with worker tenure at the firm. For parent firms, our model predicts that a worker's departure hazard to join a spinoff initially increases with worker tenure at the parent, whereas the separation hazard for conventional quits and layoffs decreases with worker tenure at the parent as in Jovanovic (1979). All these predictions are clearly supported in Brazilian data for the period 1995-2001.

Keywords: Employee spinoffs; entrepreneurship; firm performance; labor turnover

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1 Introduction

Firms bring people together, in ways both planned and unplanned. By greatly increasing the frequency of interactions, a firm allows its employees to learn more about each other's capabilities and preferences. This information, or *social capital*, can prove useful to one or more employees with an idea that is best exploited at a newly formed firm. The worker-entrepreneurs can try to lure away those of their co-workers who they believe will be most productive in the new enterprise. We refer to the employee entrepreneurs and those of their colleagues who they succeed in hiring as the *founding team* of an employee spinoff from a parent firm.[1]

Social capital in our model gives the employees who join the spinoff firm sufficient confidence in the entrepreneurs' idea and their match with it to leave their jobs and found a new formal sector enterprise. At the same time, we take a conservative approach to the value generated by this social capital compared to the literature that connects teams to spinoff performance. In our model the value of social capital is realized by improving the match between workers and jobs. It accrues entirely to the workers who move from the parent to the spinoff (as opposed to the other workers hired by the spinoff), without affecting firm performance. We do not rule out a connection between team characteristics and spinoff performance as measured, for instance, by firm survival. We simply note that it is difficult to identify such a connection when one can argue that entrepreneurs with a better idea can attract a better founding team.

To model the spinoff's recruitment, we extend the Jovanovic (1979) theory of job matching and worker turnover to allow employees to learn about their colleagues' qualities faster than their employer. Our model predicts that, for these former colleagues, the hazard rate of separation from the spinoff will be lower than for spinoff workers not hired from the parent firm at founding, and that this difference will shrink with tenure at the spinoff. These predictions are strongly supported in Brazilian data for the period 1995-2001. We complement that evidence on work trajectories at spinoffs with evidence on employee separation from parents. As our theory implies for parents, the probability that an employee leaves a parent to join a spinoff initially increases with tenure at the parent, because the spinoff entrepreneurs learn employee match quality faster. On the other hand, the probability that an employee leaves a parent for a spinoff eventually decreases with tenure, because only employees who are well matched to the parent remain.

There is a substantial literature on employee spinoffs, which has been primarily concerned with explaining why they occur and investigating their performance. This literature initially focused on high-tech spinoffs (Anton and Yao 1995, Klepper 2001). As the ubiquity of the spinoff phenomenon has become apparent, the literature has broadened to encompass employee spinoffs in other sectors (Eriksson and Kuhn 2006). The papers on teams and spinoff performance have followed this pattern. For example, Eisenhardt and Schoonhoven (1990) investigate semiconductor firms and report (p. 510), "[g]reater previous joint work experience among the founding team is associated with higher growth among new firms." Phillips (2002) investigates law firms and finds that the larger are the founding teams in proportion to their new firm, and the higher was their rank

[1] Holmstrom (1982, p. 325) defines a team as "a group of individuals who are organized so that their productive inputs are related." In our model all members of the founding team have high match quality with the entrepreneurs' idea but otherwise their productive inputs are not related. Unlike the vast literature building upon Holmstrom's article, our main interests are in the process of founding team formation rather than in the incentive structures used to elicit output from a given team.

in their previous employer, the more likely is the new firm to survive.

In the next section we develop our model of how employee spinoffs mobilize social capital. Section 3 describes our data and method of identifying spinoff firms. We present our results for retention rates at spinoffs in section 4, comparing the spinoff employees hired from the parent to the spinoff's other hires. We report our results for workers at parent firms in section 5, comparing the tenure of workers who join spinoffs to that of workers who do not. Section 6 concludes.

2 Model

2.1 Basics

Our model builds upon the influential Jovanovic (1979) theory of job matching and employee turnover. Jovanovic considers the evolution of one match between an employer and an employee. At the time of hiring, employer and employee are uncertain about the quality of the match between them. A process of Bayesian updating ensues, in which (roughly speaking) good signals cause the wage to increase, and bad signals cause the wage to fall, ultimately leading to separation. The key results are that, on average, wages rise with employee tenure and the hazard rate of separation falls because surviving matches have been selected for high quality.

Our first extension of Jovanovic (1979) is to allow for multi-employee firms: instead of one worker, each firm employs a unit measure of workers. We assume that there are constant returns to scale in production and that labor is the only input to production. It follows that the output of any employee in a firm is additively separable from that of every other employee. Nevertheless, it is important to know at which firm employees are working because we assume that an employee can only learn about the characteristics of other employees at the same firm.

Our second extension of Jovanovic (1979) is to allow for the possibility of employee entrepreneurship. A small fraction of employees in a firm may get an idea for a new firm, forming an entrepreneurial partnership. We assume that these employees can best exploit their idea outside the boundary of the existing *parent* firm because of contracting or incentive problems within the firm (Anton and Yao 1995) or because their new business plan is a poor fit for their employer (Henderson and Clark 1990, Tushman and Anderson 1986). We also assume that when their idea arrives the *spinoff* entrepreneurs learn about the match qualities of their colleagues with their planned firm through their interactions in the workplace.

For those colleagues with whom they work closely, the potential entrepreneurs learn match qualities with their planned spinoff firm faster than their current employer learns the same employees' match qualities with the existing parent firm. Since we do not observe the arrival of the entrepreneurs' idea, we simply assume that all of their learning takes place at the moment when the idea arrives. An advantage of this formulation is that it allows for the possibility that, when their idea arrives, the state of the entrepreneurs' knowledge of their colleagues is such that they already recognize who will be a good match for their planned firm. A spinoff firm thus has the potential to hire employees known to be of high match quality, a possibility that does not arise in Jovanovic (1979).

In the spirit of Lancaster (1966) we can think of employees as bundling desirable characteristics such as manual dexterity, reliability, carefulness, perseverance, friendliness, intelligence, and

so forth in different proportions. The match between an employee and a job is determined by how well this mix of characteristics fits the needs of the position. This interpretation of employee characteristics is also close to a recent extension of the workhorse model of firm-specific human capital, in which all worker skills are general but firms demand skills in differently weighted combinations (Lazear 2003). It is important to distinguish our matching approach that emphasizes "chemistry" from an alternative, in which employees have innately high or low ability and firms do not weight skill sets in different combinations. In that alternative, an offer by the spinoff firm to recruit employees from the parent would publicly reveal that they have high ability, negating the value of having learned about them faster.[2] The same does not hold if the new job is different from the old job, even if only because the context is different in the new firm. Thus under the alternative hypothesis the spinoff firm would need to be more productive than its parent in order to bid away high ability workers, whereas we will retain the assumption of Jovanovic (1979) that all firms have the same productivity. We will consider the relevance of the alternative hypothesis in our empirical work.

2.2 Employer learning

To make room for our extensions, we radically simplify the Jovanovic (1979) model of employer learning. Following Moscarini (2005) we allow match quality to take on only two values, high and low. A high-quality match produces a flow of output μ_H in continuous time and a low-quality match generates output $\mu_L < \mu_H$, where μ_H and μ_L are identical across firms. Output is also homogeneous across firms so every job produces either μ_H or μ_L, irrespective of firm age and other employer characteristics. Employers and employees are risk-neutral optimizers who discount future payoffs at the interest rate r.

Employers continuously observe the flow of output from their firms, but information about the output of any individual employee only arrives at Poisson rate ϕ. This information reveals whether the quality of the match between the employee and the firm is high or low. We add to this Poisson process another that is already present in Moscarini (2005), in which employer and employee exogenously separate at rate δ, for example because a spouse is relocated.

Workers are matched randomly to vacancies. Denote by p_0 the probability that an employee matched randomly to a vacancy will be a high quality match for the hiring firm. Denote by $q_i(t)$ the proportion of employees in firm i of *unknown match quality* at firm age t. Let us provisionally assume that an employee whose match is revealed to be low quality separates from the firm (for the derivation of quits see below). Then output $x_i(t)$ of firm i at age t is

$$x_i(t) = q_i(t)[(1-p_0)\mu_L + p_0\,\mu_H] + [1-q_i(t)]\,\mu_H \tag{1}$$

because there is a unit measure of employees at every firm.

We follow Jovanovic and consider wage outcomes where every employee receives his expected marginal product. We can then compactly express any employee's wage as

$$w(p) = (1-p)\mu_L + p\,\mu_H, \text{ where } \begin{cases} p = p_0 & \text{before match quality is revealed,} \\ p = 1 & \text{as soon as match quality is revealed.} \end{cases} \tag{2}$$

[2]We should also note that this alternative hypothesis would have difficulty explaining how employees with low ability remain in the labor force.

Because workers are matched randomly to vacancies, $p = p_0$ at the time of hiring. As soon as the firm learns about an employee's match quality, p is reset to 1 or zero. In the former case of revealed high match quality, the employee is promoted with a pay raise from $w(p_0)$ to $w(1) = \mu_H > w(p_0)$. In the latter case of revealed low match quality, the employee would be demoted to $w(0) = \mu_L$ and therefore chooses to quit because an existing outside employer will pay $w(p_0) > \mu_L$ at hiring.[3] There is no forgetting, so an employee's wage at a given firm i weakly rises over time.

Now consider a tenure cohort within a firm, that is, a strictly positive measure of employees with identical tenure. As time progresses, learning strictly changes the tenure cohort's average wage and its average hazard rate of separation. For any individual worker, the wage only weakly increases with tenure and both the endogenous hazard of quitting $\phi(1-p_0)$ and the exogenous hazard of dissolution δ are constant. For a cohort of workers who are still employed at the same firm, however, the fraction with known match quality strictly increases with tenure because workers with revealed match quality quit if and only if their match has low quality. It follows that a cohort's average wage strictly increases with tenure, and that its average hazard rate of separation strictly decreases because the rate of endogenous quitting falls as the fraction of workers with known match quality in the cohort increases. We summarize these findings in a Lemma.

Lemma 1. *For any cohort of employees with tenure τ at a firm i, the average wage strictly increases and the average hazard rate of separation strictly decreases with tenure.*

Proof. Denote by $S_i(\tau)$ the size of the cohort with tenure τ at a firm i, and by $q_i(\tau) \equiv S_i^q(\tau)/S_i(\tau)$ the fraction of employees whose match quality is unknown in that cohort. The measure of cohort workers with unknown match quality (but still employed at firm i) shrinks at rate $\dot{S}_i^q(\tau)/S_i^q(\tau) = -(\delta+\phi)$, while the size of the whole cohort shrinks at rate $\dot{S}_i(\tau)/S_i(\tau) = -[\delta+\phi(1-p_0)q_i(\tau)]$ because a fraction $\phi(1-p_0)$ of cohort members with unknown match quality are discovered to have low match quality and quit. By definition of $q_i(\tau)$, its relative rate of change is $\dot{q}_i(\tau)/q_i(\tau) = \dot{S}_i^q(\tau)/S_i^q(\tau) - \dot{S}_i(\tau)/S_i(\tau)$, so we can use the above relationships to obtain

$$\dot{q}_i(\tau)/q_i(\tau) = -\phi\,[1 - (1-p_0)q_i(\tau)] < 0.$$

The fraction of cohort employees with unknown match quality declines with tenure at an accelerating rate that approaches $-\phi$ in the limit.

The average wage of a cohort of tenure τ at firm i is $q_i(\tau)w(p_0) + [1-q_i(\tau)]w(1) = w(1) - q_i(\tau)[w(1)-w(p_0)]$, where $w(\cdot)$ is given by equation (2). The share $q_i(\tau)$ strictly declines in τ, so the average cohort wage strictly increases with tenure. The average hazard rate of separation of the cohort is $q_i(\tau)[\delta+\phi(1-p_0)] + [1-q_i(\tau)]\delta = \delta + q_i(\tau)\phi(1-p_0)$. As $q_i(\tau)$ strictly declines with tenure, the cohort average hazard rate of separation strictly decreases. □

Having obtained the results of Jovanovic (1979) that are most important for our purposes, we turn to employee spinoff firms and the process by which they are formed.

[3] In the full general-equilibrium model, a worker who quits initially shifts into unemployment. The precise condition for an endogenous quit is that the flow value of unemployment weakly exceeds the flow value of employment with $w(0) = \mu_L$(see Subsections 2.4 and 2.6).

2.3 Spinoff entrepreneurship and intrafirm social capital

An incumbent firm experiences an innovation shock at a Poisson rate 2θ. With probability one-half the shock results in a new idea that will lead a share of current workers at the firm to leave and start an employee spinoff firm. In this case, the parent firm survives and rehires workers to fill the vacancies. With probability one-half the shock is severe and results in firm exit. Hence spinoffs are created at a Poisson rate θ and incumbent firms exit at the same rate θ. We choose this setup of equal entry and exit rates so as to retain a constant measure of firms.

Now consider the entry of an employee spinoff. At Poisson rate θ a constant fraction γ of the employees in the parent firm gets an idea for a new firm. We will refer to these workers-turned-entrepreneurs as the *partners*. The partners are drawn with an equal chance from the employees with known and with unknown match quality.

Neither owners of firms nor the profits they receive are recorded in our data. Accordingly, we simplify the treatment of partners and profits in our model in order to make room for details in the parts of our model that address our data. We assume that the output market is perfectly competitive, which in combination with equations (1) and (2) ensures that all firms earn zero profits. In lieu of profits, each partner gets a flow value a from implementing the idea for the new firm, which we interpret as the monetary value of the utility of being one's own boss. We assume $a > \mu_H$ so that all ideas are implemented: an individual always prefers being a partner to being an employee. This would clearly be a bad assumption if our goal was to predict spinoffs. The relevant predictions of our model will only concern the contrast between a spinoff's hires from the parent and from elsewhere, on the one hand, and between those hires and the employees who remain at the parent, on the other.

Next consider the $(1-\gamma)$ parent employees who are not partners. Of these, a fraction α belongs to the *social network* of the partnership. These are the employees whose match qualities with the new firm are known to the partners. For our benchmark model, we assume that employees are randomly assigned to social networks at time of hiring (we relax this assumption for the empirics). It follows that a share p_0 of the employees in the partners' social network will be high quality matches at the spinoff. Intuitively, if my social network predates my idea for a new firm, I cannot select colleagues to be in my network based on their match quality with my new firm. Thus, when my idea arrives, the probability that a member of my social network is of high match quality is the same as for the general population of workers.

We assume that the partners succeed in recruiting an employee from the parent to their new firm if and only if they offer him a strictly better contract. It follows immediately that the spinoff firm hires $q_i(t)(1-\gamma)\alpha p_0$ employees from the parent firm because they earn only $w(p_0)$ at the parent but they will earn $w(1) = \mu_H > w(p_0)$ at the spinoff.[4] Note that the partnership cannot offer a better contract to any employee outside the social network because the spinoff cannot offer a higher wage than the parent firm, nor can it offer a better contract to any employee of known match quality with the parent firm because these employees already receive the highest possible wage $w(1) = \mu_H$ and will continue to receive $w(1)$ until exogenous separation occurs. In the empirical work below we call the employees recruited from the parent to the spinoff firm *team members*, and we consider these employees and the partners to constitute the *founding team* of the new firm.

[4]We could allow an offer by the spinoff to raise the probability that an employee is of high match quality with the parent from p_0 to any value less than one.

The augmented model with social capital and spinoff entrepreneurship preserves the properties of Lemma 1 for cohorts of workers at the parent firm.

Lemma 2. *The fraction of cohort employees at a firm i with unknown match quality strictly declines with the cohort's tenure τ at an accelerating rate that approaches $-[\theta(1-\gamma)\alpha p_0 + \phi]$ as tenure becomes arbitrarily high. The cohort's average wage strictly increases and the cohort's average hazard rate of separation strictly decreases with tenure.*

Proof. Denote by $S_i(\tau)$ the size of the cohort with tenure τ at a firm i, and by $q_i(\tau) \equiv S_i^q(\tau)/S_i(\tau)$ the fraction of employees whose match quality is unknown in that cohort. The measure of cohort workers with unknown match quality (but still employed at surviving firm i) strictly shrinks at rate $\dot{S}_i^q(\tau)/S_i^q(\tau) = -[\delta + \theta\gamma + \theta(1-\gamma)\alpha p_0 + \phi]$, while the size of the whole cohort shrinks at rate $\dot{S}_i(\tau)/S_i(\tau) = -\{\delta + \theta\gamma + [\theta(1-\gamma)\alpha p_0 + \phi(1-p_0)]q_i(\tau)\}$ because a fraction $\theta(1-\gamma)\alpha p_0$ of cohort members with unknown match quality belong to a spinoff entrepreneur's network and expect a strictly higher wage at her new firm, while a fraction $\phi(1-p_0)$ of cohort members with unknown match quality are discovered to have low match quality and quit. By definition of $q_i(\tau)$, its relative rate of change is $\dot{q}_i(\tau)/q_i(\tau) = \dot{S}_i^q(\tau)/S_i^q(\tau) - \dot{S}_i(\tau)/S_i(\tau)$ so, using the above relationships,

$$\dot{q}_i(\tau)/q_i(\tau) = -\theta(1-\gamma)\alpha p_0[1-q_i(\tau)] - \phi\,[1-(1-p_0)q_i(\tau)] < 0.$$

The rate of change strictly accelerates with tenure because $\partial[\dot{q}_i(\tau)/q_i(\tau)]/\partial q_i(\tau) = \theta(1-\gamma)\alpha p_0 + \phi(1-p_0) > 0$. For arbitrarily high tenure, $\lim_{\tau\to\infty} \dot{q}_i(\tau)/q_i(\tau) = -\theta(1-\gamma)\alpha p_0 - \phi$. On the other hand, $q_i(\cdot)$ is strictly bounded away from one in the presence of social capital so the rate of change is bounded by $-[\theta(1-\gamma)\alpha p_0 + \phi] < \dot{q}_i(\tau)/q_i(\tau) < -\phi p_0$. □

Compared to the model without social capital and entrepreneurship, the share of cohort employees with unknown match quality declines even faster under spinoff entrepreneurship because there are now two sources of learning: employers learn at rate ϕ and spinoff entrepreneurs learn about their $(1-\gamma)$ co-workers at rate $\theta\alpha$.

Having extended our model of learning at the parent firm, we now turn back to the spinoff firm. Like any firm, the spinoff employs a unit mass of employees in total. It must therefore hire $1-q_i(t)(1-\gamma)\alpha p_0$ additional employees, drawing from the current pool of displaced employees who either worked for dissolved firms, exogenously separated from active firms, or endogenously quit active firms because of a revealed low match quality.[5] At hiring, the match quality of outside employees or *non-team workers* is unknown and they receive a wage $w(p_0)$.

We conclude our description of the spinoff process by relaxing, for the sake of empirical realism, our assumption that social network members recruited to a planned spinoff firm are high quality matches for the new jobs with certainty. Instead we allow for *hiring error* that could arise because, although the partnership envisions positions for everyone recruited for the spinoff for which they are perfect fits, the configuration of the new firm is uncertain and some of these positions may not turn out as conceived. In this case the unlucky recruits may or may not fit the positions that are actually available. Concretely, we assume that at the time of spinoff entry a share

[5] Applying the rule that recruiting employees from other firms requires offering a strictly better contract, we see that recruitment of team members from a parent to a spinoff firm is the only instance of poaching employees from other active firms that can occur in our model.

ε of employees who leave the parent to join the spinoff have the same probability of high match quality as workers hired from the outside,[6] where ε is a random variable with support (0,1).[7] The realization of ε is revealed to potential recruits at the time of spinoff hiring and can be thought of as a characteristic of the idea that initiates the firm. It matters only at birth of the firm, when it helps to determine the initial division of employees between known and unknown match quality.[8]

To complete the specification of our model we describe unemployment. As in Moscarini (2005), any unemployed worker earns a flow value of b from home production, self-employment or the informal sector. Unemployed workers are matched to vacancies at the Poisson job finding rate λ. The flow value of unemployment b must be small enough that a worker will accept a new job when one becomes available, but large enough that an employee prefers to quit his current job when he is poorly matched. We derive the bounds on b for given λ in the next subsection. The job finding rate λ in turn is determined in general equilibrium so that the flow of employees out of unemployment equals the flow into unemployment, and we derive it in Subsection 2.6 below.

2.4 Individual dynamics

Let P be an individual's value of being a spinoff partner, and let $V(p_0)$ and $V(1)$ be an individual's value of employment with unknown and known match quality, respectively. Workers in our data leave the formal sector for informal work, self employment or unemployment, so we allow for a status outside formal work and call its value U. Denoting the expected hiring error by $\bar{\varepsilon} \equiv \mathbb{E}[\varepsilon]$, we can express the Bellman equations for an individual compactly as:

$$\begin{aligned} r\,V(p) \;=\; & w(p) - (\delta+\theta)\,[V(p)-U] \\ & +\phi\big\{p\,[V(1)-V(p)] - (1-p)\,[V(p)-U]\,\big\} \\ & +\theta\big\{\gamma\,[P-V(p)] \\ & \qquad +(1-\gamma)\alpha p_0 \max\left[0,(1-\bar{\varepsilon})V(1)+\bar{\varepsilon}V(p_0)-V(p)\right]\big\} \end{aligned} \tag{3}$$

with $p \in \{p_0, 1\}$, where

$$r\,U = b + \lambda[V(p_0) - U], \tag{4}$$

and

$$r\,P = a - \theta[P - U]. \tag{5}$$

We can solve these four equations in four unknowns conditional on the value of the job finding

[6] Recalling our Lancasterian conception of employees, we suppose the partners did not learn about their characteristics along the dimensions relevant to the positions actually available because these were not relevant for the planned positions.

[7] We could still allow an offer by the spinoff to raise the probability that an employee is of high match quality with the parent from p_0 to p_1, say, provided p_1 always satisfies $w(p_1) < (1-\varepsilon)w(1) + \varepsilon w(p_0)$. In our empirical work we use operation of the spinoff in a different industry than the parent to indicate greater hiring error, which is also when we expect spinoff recruitment to be less informative about parent match quality.

[8] Hiring error could be specified in other ways that would have the same empirical implications but would make solution of the model more difficult.

rate λ. Simplifying (3) through (5), an intermediate step in the solution yields:

$$V(p_0) = \frac{w(p_0) + [\phi + \theta(1-\gamma)\alpha(1-\bar{\varepsilon})]p_0 V(1) + \theta\gamma P + [\delta + \theta + \phi(1-p_0)]U}{r + [\phi + \theta(1-\gamma)\alpha(1-\bar{\varepsilon})]p_0 + \theta\gamma + [\delta + \theta + \phi(1-p_0)]}, \quad (6)$$

$$V(1) = \frac{\mu_H + \theta\gamma P + (\delta + \theta)U}{r + \theta\gamma + (\delta + \theta)}, \quad (7)$$

$$U = \frac{b + \lambda V(p_0)}{r + \lambda}, \quad (8)$$

$$P = \frac{a + \theta U}{r + \theta}. \quad (9)$$

Equation (6) summarizes the vicissitudes to which an individual in our model is subject. When he is of unknown match quality, perhaps having just been matched randomly to a vacancy, he receives the expected wage $w(p_0)$ given by equation (2). With probability ϕp_0 he is recognized as having high match quality by his current employer and with probability $\theta(1-\gamma)\alpha p_0(1-\bar{\varepsilon})$ he is recruited by members of his social network into their new firm, for which they have accurately judged him to be of high match quality. With probability $\theta\gamma$ he is struck by an idea for a new firm himself. Finally, with probability $\phi(1-p_0)$ he is revealed to have low match quality with his current employer, with probability δ he is exogenously separated from his current employer, and with probability θ his current employer exits.

The four equations (6)-(9) form a conventional linear system in the four unknowns $V(p_0)$, $V(1)$, U and P. The solutions are straightforward and we report them in Appendix B.

In equilibrium, the flow value a from implementing a spinoff idea and the flow value b of unemployment must satisfy certain parameter restrictions so that $P > V(1)$, $V(p_0) > U$ and $U \geq V(0)$. Under these respective conditions, an employee with a spinoff idea will quit to found a new firm, an employee will strictly prefer formal employment over unemployment and an employee whose match is revealed to be low quality will quit for unemployment instead of being demoted. By equations (7) and (9), $P > V(1)$ if and only if $a > [(r+\theta)\mu + r\delta U]/(r+\delta+\theta)$. By equation (8), $U < V(p_0)$ if and only if $b < rV(p_0)$. Similarly by (8), $U \geq V(0)$ if and only if $b \geq rV(0) - \lambda[V(p_0) - V(0)]$. We can freely choose a value of b such that $rV(0) - \lambda[V(p_0) - V(0)] \leq b < rV(p_0)$ because $V(0) < V(p_0)$ and because λ is not a function of b in equilibrium (see Subsection 2.6). This value of b in turn determines the lower bound on a as stated above. For solutions in terms of fundamentals see Appendix B.

2.5 Firm dynamics

We have seen that the ability of spinoff entrepreneurs (the partners) to mobilize social capital for their new firm depends directly on the proportion of their colleagues whose match quality with the current employer is unknown. We now show how this proportion $q_i(t)$ evolves with the age t of firm i. At any moment the flow of employees out of unknown into known status at firm i is $q_i(t)\,\phi\,p_0$. The flow of employees into unknown status is $[1-q_i(t)]\,\delta + [1-q_i(t)]\,\theta\gamma$.[9] It follows

[9]To see this rigorously, observe that at any moment in time, an incumbent firm loses a measure δ of workers because of exogenous separation. These workers are instantaneously replaced with outside workers of unknown match quality. Among the separating workers, a measure $[1-q_i(t)]\delta$ was of known match quality at the firm so $q_i(t)$ increases at a rate

that the change in the fraction of workers with unknown match quality is

$$\dot{q}_i(t) = [1-q_i(t)]\,(\delta + \theta\gamma) - q_i(t)\,\phi\,p_0 \tag{10}$$

and it depends negatively on $q_i(t)$. Thus, from any initial value, $q_i(t)$ will ultimately converge to its firm-level steady state value q^* at which $\dot{q}_i(t) = 0$, where

$$q^* = \frac{\delta + \theta\gamma}{\delta + \theta\gamma + \phi\,p_0}. \tag{11}$$

As we expect, the steady state proportion of workers with unknown match quality at a firm increases with the exogenous separation rate δ and the rate of spinoff entrepreneurship $\theta\gamma$ and decreases with the rate of information arrival ϕ.

Equation (10) is a linear first-order non-homogeneous differential equation. Its solution can be written

$$q_i(t) - q^* = C_{i0}\exp\{-(\delta + \theta\gamma + \phi\,p_0)t\}, \tag{12}$$

for the initial condition that $q_i(0) = C_{i0} + q^*$ at a firm's birth. The spinoff process determines a firm i's initial share $q_i(0)$ of employees with unknown match quality. Denote the parent's share of employees with unknown match quality by $q_p(t_{i0})$, where t_{i0} is the parent's age at the time when firm i spins off.[10] At the spinoff i, a measure $q_p(t_{i0})(1-\gamma)\alpha p_0(1-\varepsilon)$ are founding team members with known match quality.[11] This implies that a spinoff i's initial share $q_i(0)$ of employees with unknown match quality must be

$$q_i(0) = 1 - q_p(t_{i0})(1-\gamma)\alpha p_0(1-\varepsilon). \tag{13}$$

The larger the parent's share of employees with unknown match quality, the smaller the share of employees with unknown match quality at the spinoff, because the partners are able to recruit a larger fraction of their network for their new firm. Using (13) in (12), we find the evolution of the spinoff's share of employees with unknown quality at firm age t

$$q_i(t) - q^* = [1 - q_p(t_{i0})(1-\gamma)\alpha p_0(1-\varepsilon) - q^*]\exp\{-(\delta + \theta\gamma + \phi\,p_0)t\}, \tag{14}$$

given the parent's share of employees with unknown quality at time of spinoff birth $t = 0$ when the parent's age was t_{i0}.

$[1-q_i(t)]\delta$ from this flow. Similarly, an incumbent firm loses a measure $\theta\gamma$ of workers because they become partners of a spinoff, and those are also instantaneously replaced with outside workers of unknown match quality. So $q_i(t)$ increases at a rate $[1-q_i(t)]\theta\gamma$ from that flow. Note that the $q_i(t)\theta(1-\gamma)\alpha p_0$ social network members who choose to join a spinoff must have been of unknown match quality so they cause no net change to the measure of unknown match quality workers as they are replaced with new workers of unknown quality. Similarly, the $q_i(t)\phi(1-p_0)$ employees revealed to be low quality matches were of unknown match quality before so they also cause no net change to the measure of unknown match quality workers.

[10] The new firm's measure γ of partners is drawn from the parent's employees with known match quality and with unknown match quality with equal probability: $\gamma = [1-q_p(t_{i0})]\gamma + q_p(t_{i0})\gamma$.

[11] Among the founding team members, a measure $q_p(t_{i0})(1-\gamma)\alpha p_0\varepsilon$ is of unknown match quality, and the measure $1 - q_p(t_{i0})(1-\gamma)\alpha p_0$ of outside hires is of unknown match quality.

2.6 Closing the model

We assume that the total measure of individuals is $(1+\gamma)\bar{M}$, where $\bar{M}$ is the total measure of firms and γ is the constant fraction of partners in the population. The value functions imply optimal population flows between partnership, employee status, and unemployment.

Start with partnership. At any moment in time, a measure $\theta\gamma\bar{M}$ of employees turns into partners at a spinoff. On the other hand, the exogenous death rate of firms θ causes an outflow of $\theta\gamma\bar{M}$ from partnerships into unemployment at any given moment. Thus the net flow of individuals into and out of partnership is zero at any moment.

Consider unemployment next. A measure $\theta\gamma\bar{M}$ of individuals flows from partnerships into unemployment at any moment. A measure $(\delta+\theta)\bar{M}$ of workers is exogenously separated from employment while a measure $\phi(1-p_0)\bar{q}\bar{M}$ endogenously quits as their match quality is revealed to be low, where $\bar{q}$ is the economy-wide fraction of employees with unknown match quality. For the economy to be in equilibrium, the flows into unemployment must be balanced by flows out of unemployment, yielding

$$\lambda = \delta + \theta(1+\gamma) + \phi(1-p_0)\bar{q}. \tag{15}$$

A similar argument applies to inflows and outflows from employment. A measure $\lambda\bar{M} = [\theta(1+\gamma) + \delta + \phi(1-p_0)\bar{q}]\bar{M}$ flows from unemployment into employment at any moment. A measure $\theta\gamma\bar{M}$ of workers flows out of employment into partnerships at any moment, and a measure $(\delta+\theta)\bar{M} + \phi(1-p_0)\bar{q}\bar{M}$ of workers flows out of employment into unemployment at any moment.

Different unemployment levels are consistent with this equilibrium: for a total measure of $(1+\gamma)\bar{M}$ persons in the population, unemployment is zero. For a total measure of $(1+\gamma+u)\bar{M}$ persons in the population, the unemployment level is $u\bar{M}$, and u can be chosen arbitrarily.

It remains to solve for $\bar{q}$, which depends on the steady-state distribution of q across the population of firms. In a future draft we will prove that this distribution exists, which implies that $\bar{q}$ exists since q is bounded between zero and one. For now we note the existence of a self-replicating benchmark case where the steady-state distribution of q collapses to q^*. This special case requires that $q_i(0) = q^*$ for all i. Recall that a spinoff i's initial share $q_i(0)$ of employees with unknown match quality must be

$$q_i(0) = 1 - q_p(t_{i0})(1-\gamma)\alpha p_0(1-\varepsilon)$$

by equation (13). In the special case we replace $q_i(0)$ and $q_p(t_{i0})$ in (13) with q^*, and solve for

$$\alpha^* = (1-q^*)/q^*(1-\gamma)p_0(1-\varepsilon), \tag{16}$$

where α^* is the level of social capital that causes the steady state distribution of q to collapse to q^*. We see that the special case can only arise when $q^* > {}^1\!/_2$.

2.7 The contribution of social capital to aggregate output

In our model aggregate output is

$$\bar{X} = \bar{M}\bar{x} = \bar{M}\left\{\bar{q}[(1-p_0)\mu_L + p_0\,\mu_H] + (1-\bar{q})\mu_H\right\}, \tag{17}$$

where we used equation (1) to substitute for $\bar{x}$.[12] Aggregate output $\bar{X}$ increases as the economy-wide fraction of workers with unknown match quality $\bar{q}$ drops. Social capital therefore contributes to aggregate output by reducing the initial share of workers of unknown type for every firm and thereby decreasing $\bar{q}$. In the special case where $\alpha = \alpha^*$, social capital reduces $\bar{q}$ to q^*. Intuitively, the contribution of social capital to aggregate output should increase with network size α. The larger an employee's network at a parent, the larger the fraction of workers with known match quality at spinoff startup.

To gain further insight into the importance of social capital for aggregate performance, it is helpful to find $\bar{q}$ in the absence of social capital. We begin with the observation that $\alpha = 0$ implies $q_i(0) = 1$ for all firms i. If there is no networking at the parent, then spinoffs have to start with a completely unknown workforce. The fraction of unknown workers $q_{i,\alpha=0}(t)$ is then determined entirely by the age of the firm. From equation (14), we have

$$q_{i,\alpha=0}(t) - q^* = (1 - q^*) \exp\{-(\delta + \theta\gamma + \phi\, p_0)t\}. \tag{18}$$

The Poisson process of birth and death of firms at rate θ yields an exponential steady state distribution of firm age with parameter θ, i.e. the steady state fraction of firms with age less than t $G(t) = 1 - \exp\{-\theta t\}$. Because $q_{i,\alpha=0}(t)$ decreases monotonically with t from $q_{i,\alpha=0}(0) = 1$, it is more convenient to work with the steady state fraction $1 - G(t)$ of firms with age *greater* than t, $1 - G(t) = \exp\{-\theta t\}$. When we now change variable from t to q, we will obtain the steady state fraction of firms with share of unknown workers less than q, that is the distribution function $F_{\alpha=0}(q)$ for q. We solve for t as a function of q using equation (18). Taking natural logarithms of both sides, we have $\ln(q - q^*) = \ln(1 - q^*) - (\delta + \theta\gamma + \phi\, p_0)t$ or $t = [\ln(1 - q^*) - \ln(q - q^*)]/(\delta + \theta\gamma + \phi\, p_0)$. Making the change of variable then yields

$$\begin{aligned} 1 - G[t(q)] &= \exp\{-[\theta/(\delta+\theta\gamma+\phi p_0)][\ln(1 - q^*)]\} \exp\{[\theta/(\delta+\theta\gamma+\phi p_0)][\ln(q - q^*)]\} \\ &= (q - q^*)^{\theta/(\delta+\theta\gamma+\phi\, p_0)}/(1 - q^*)^{\theta/(\delta+\theta\gamma+\phi\, p_0)}. \end{aligned}$$

The steady state fraction of firms with a share of workers of unknown type less than q is therefore

$$F_{\alpha=0}(q) = \left(\frac{q - q^*}{1 - q^*}\right)^{\theta/(\delta+\theta\gamma+\phi\, p_0)}. \tag{19}$$

Using the density associated with this distribution function, we integrate over q between q^* and unity and obtain a remarkably simple expression for the economy-wide average q in the absence of social capital:[13]

$$\bar{q}_{\alpha=0} = \frac{\theta + (\delta+\theta\gamma+\phi\, p_0)\, q^*}{\delta + \theta(1+\gamma) + \phi\, p_0} = \frac{\delta + \theta(1+\gamma)}{\delta + \theta(1+\gamma) + \phi\, p_0}. \tag{20}$$

As the rate of decay $(\delta+\theta\gamma+\phi p_0)$ of each firm's $q_i(t)$ to the firm's long-term share of unknown workers grows large, or as the rate of firm birth and death θ becomes small, $\bar{q}_{\alpha=0}$ approaches q^* as

[12] Aggregate welfare is proportional to $\bar{M}\bar{x} + \gamma\bar{M}\, a$. The contribution of entrepreneurship $\gamma\bar{M}\, a$ is constant, so we focus on aggregate output.

[13] The density is $f(q) = [\theta/(\delta+\theta\gamma+\phi\, p_0)][1/(q - q^*)]F(q)$ so that the indeterminate integral over q becomes $\int q\, \mathrm{d}F(q) = [\theta q + (\delta+\theta\gamma+\phi\, p_0)q^*]F(q)/[\delta + \theta(1+\gamma) + \phi\, p_0]$.

given by (11), since the value of q for all but the youngest firms will be near q^* or because nearly all firms are old. On the other hand, as the rate of decay of $q_i(t)$ to its long-term value becomes small, or as the rate of firm birth and death becomes large, $\bar{q}_{\alpha=0}$ approaches unity since the value of q for all but the oldest firms will be near $q_i(0) = 1$ or because nearly all firms are young.

The larger is $\bar{q}_{\alpha=0}$ in the absence of social capital, the greater is the scope for social capital to increase aggregate output. From equation (20) we therefore see that the potential effect of social capital on aggregate output increases with the rate of spinoff creation θ and decreases with the rate of employer learning ϕ.[14] In the special case where social capital increases from zero to $\alpha = \alpha^*$, the reduction in $\bar{q}_{\alpha=0}$ attributable to social capital is $\bar{q}_{\alpha=0} - q^* = (1 - q^*)\theta/[\delta + \theta(1+\gamma) + \phi\, p_0]$.

In future drafts, we will derive properties of the general q distribution beyond those two benchmark distributions. We can then use estimates from the following sections to calibrate the model and quantify the empirical relevance of social capital in entrepreneurship.

3 Data and Identification of Employee Spinoffs

Our data derive from the linked employer-employee records RAIS (*Relação Anual de Informações Sociais* of the Brazilian labor ministry *MTE*), which record comprehensive individual employee information on occupations, demographic characteristics and earnings, along with employer identifiers. By Brazilian law, every private or public-sector employer must report this information every year.[15] De Negri, Furtado, Souza and Arbache (1998) compare labor force information in RAIS to that in a main Brazilian household survey (PNAD) and conclude that, when comparable, RAIS delivers qualitatively similar results to those in the national household survey. Menezes-Filho, Muendler and Ramey (2008) apply the Abowd, Kramarz, Margolis and Troske (2001) earnings-estimation methodology to Brazil and show that labor-market outcomes from RAIS broadly resemble those in France and the United States, even after controlling for selection into formal-sector employment, except for unusually high returns to high school and college education and to experience among males. Appendix A in Hirakawa, Muendler and Rauch (2010, hereafter HMR) presents further details on the data source.

A job observation in RAIS is identified by the employee ID, the employer's tax ID (CNPJ), and dates of job accession and separation. To avoid double-counting employees at new firms, we keep only one observation for each employer-employee pair, choosing the job with the earliest hiring date. If the employee has two jobs at the firm starting in the same month, we keep the highest paying one. The rules on tax ID assignments make it possible to identify new firms (the first eight digits of the tax ID) and new plants within firms (the last six digits of the tax ID). Appendix A

[14] $\bar{q}_{\alpha=0}$ also increases with the rate of exogenous employee separation δ, but higher δ also tends to negate the impact of social capital by ridding firms of their high match quality employees.

[15] RAIS primarily provides information to a federal wage supplement program (*Abono Salarial*), by which every employee with formal employment during the calendar year receives the equivalent of a monthly minimum wage. RAIS records are then shared across government agencies. An employer's failure to report complete workforce information can, in principle, result in fines proportional to the workforce size, but fines are rarely issued. In practice, employees and employers have strong incentives to ascertain complete RAIS records because payment of the annual public wage supplement is exclusively based on RAIS. The ministry of labor estimates that well above 90 percent of all formally employed individuals in Brazil are covered in RAIS throughout the 1990s. Data collection is typically concluded by March following the year of observation.

discusses the relevant details on tax ID assignment. Our pristine RAIS records include 71.1 million employees (with 556.3 million job spells) at 5.52 million plants in 3.75 million firms over the sixteen-year period 1986-2001 in any sector of the economy. We limit our attention to the years 1995-2001 and use the period 1986-1994 in RAIS to ensure that firms we label as new in 1995-2001 have not operated before. Moreover, RAIS does not specify the legal form of firms until 1995, information that is needed to carefully identify employee spinoffs as described below. During this 7-year period, 1.54 million new firms and 2.17 million plants entered (of which 581 thousand new plants were created within incumbent firms).

By 1995 macroeconomic stabilization had succeeded in Brazil. The Plano Real from August 1994 had brought inflation down to single-digit rates. Fernando Henrique Cardoso, who had enacted the Plano Real as Minister of Finance, became president, signalling a period of financial calm and fiscal austerity. Apart from a large exchange-rate devaluation in early 1999 and a subsequent switch from exchange-rate to inflation-targeting at the central bank, macroeconomic conditions remained relatively stable throughout the period.

In order to test our predictions it is crucial that we successfully identify employee spinoff firms and their parents and distinguish employee-initiated founding teams from those formed by employers. HMR restrict their attention to new firms with at least five employees and use the criterion that if at least one quarter of the workers at a new firm previously worked for the same existing firm, the new firm is an employee spinoff and the existing firm is its parent.[16] However, if this new firm absorbed at least seventy percent of the workers in one of the parent's plants and has a legal form such that it could be owned by the parent, HMR classify it as a divestiture (an employer-initiated spinoff) rather than an employee spinoff. HMR find that the performance of spinoffs is superior to new firms without parents but inferior to divestitures. In particular, HMR document that size at entry is larger for employee spinoffs than for new firms without parents but smaller than for divestitures, and that subsequent exit rates for employee spinoffs are smaller than for new firms without parents but larger than for divestitures. These results are consistent with the interpretation that some part of a parent firm's productivity is embodied in its employees and portable by them to a new firm. We will use HMR's criteria to distinguish employee spinoffs from new firms without parents and from divestitures. By these criteria, roughly 30 percent of new Brazilian firms in the period 1995-2001 with at least five employees are employee spinoffs.

4 Retention Hazards at Spinoffs

For the empirical analysis we find it convenient to work with the *retention hazards* of team members and non-team workers, where the retention hazard equals one less the separation hazard. We define the *retention hazard gap* as the difference between the retention hazards of team members and non-team workers, conditional on survival of the spinoff firm that employs them.

Our model makes two predictions regarding the retention hazard gap.

Proposition 1. *The retention hazard gap between team members and non-team workers at time of hiring is positive and diminishes with tenure.*

[16] See HMR for more details of this method and for robustness of results to an alternative method of identifying spinoff firms.

Proof. Let us define $q_{i0}(\tau)$ as the proportion of the employee cohort with tenure τ that was of unknown match quality with firm i when it was founded (time 0) and that is still of unknown match quality. Note that $q_{i0}(0) = 1$. The average hazard rate of separation for this cohort is $q_{i0}(\tau)[\delta+\phi(1-p_0)+\theta(\gamma+(1-\gamma)\alpha p_0)]+[1-q_{i0}(\tau)](\delta+\theta\gamma) = \delta+\theta\gamma+q_{i0}(\tau)[\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]$. This is the average separation hazard for non-team workers, which we can denote by $s_n(\tau)$. The average separation hazard for team members is then given by $(1-\varepsilon)(\delta+\theta\gamma)+\varepsilon s_n(\tau)$. The difference between the average separation hazards for non-team workers and team members is easily shown to be $(1-\varepsilon)[s_n(\tau)-(\delta+\theta\gamma)] = (1-\varepsilon)[\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]\, q_{i0}(\tau) > 0$. Moreover, by Lemma 2 we have $\dot{q}_{i0}(\tau) < 0$, so the difference diminishes with tenure. □

Proposition 2. *As ε increases, the retention hazard gap between team members and non-team workers at time of hiring decreases but the rate at which it diminishes with tenure also decreases.*

Proof. The difference between the average separation hazards for non-team workers and team members is $(1-\varepsilon)[\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]\, q_{i0}(\tau)$ and the rate at which it diminishes with tenure is $(1-\varepsilon)[\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]\dot{q}_{i0}(\tau)$, where $\dot{q}_{i0}(\tau) < 0$ by Lemma 2. □

In an alternative, perfect information world, it is hardly likely that entrepreneurs would find the best workers for their new firm among the relative handful available at their current employer. They might nevertheless choose them to conserve on upfront hiring costs, and gradually replace them with better workers as their firm matures, causing Proposition 1 to fail. In other words, contrary to our explanation of the spinoff process, workers hired from the parent could be negatively selected. Muendler and Rauch (2011) present evidence that, when locating customers and inputs, spinoff firms remain geographically closer to their parents than new plants that a parent sets up within the firm, which is consistent with a desire to reduce hiring costs by recruiting from the parent.

We begin by testing our predictions using a parsimonious empirical specification that retains our model's assumption that workers are homogeneous except for their match qualities. We then relax this assumption and add variables to control for worker heterogeneity.

Table 1 shows linear regressions where the dependent variable is the proportion of workers, divided between team members and others, who remain employed at a spinoff firm from one year to the next.[17] Note that all these employees joined the new firm in the same year. The key explanatory variable is an indicator for team members.[18] We also include an indicator that equals one if the employee spinoff is in a different four-digit *CNAE* industry from the parent firm (which happens in about half of all cases), and the interaction between this indicator and the indicator for team members.[19] The interaction is our attempt to compare the retention hazard gaps between spinoff firms with different hiring errors (realizations of ε). It is reasonable to think that the

[17] Because our model applies to permanent rather than temporary separation, any worker who is still with the firm at the end of our sample period (2001) is counted in the numerator, even if he is not with the firm in one or more intervening years.

[18] If the partners from our model choose to pay themselves salaries and therefore incur payroll taxes, they will be recorded as team members in our data. We believe that this rarely happens, but as a robustness check we reran Table 1 excluding team members with occupations coded as director or manager. Our results were qualitatively unchanged.

[19] The coefficients on the team indicator are not qualitatively affected by the exclusion of these variables.

Table 1: RETENTION HAZARD GAP AT SPINOFF

	All workers					
Share of retained workers	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Team member	.072	.117	.066	.052	.046	.030
	(.002)***	(.003)***	(.004)***	(.006)***	(.008)***	(.014)**
Different *CNAE*	-.003	.011	.0006	.014	-.003	.003
	(.002)	(.003)***	(.005)	(.006)**	(.009)	(.016)
Team member × Different *CNAE*	-.022	-.033	-.015	-.016	-.010	-.015
	(.003)***	(.005)***	(.006)**	(.008)*	(.012)	(.019)
Obs.	120,886	83,028	46,578	24,938	11,222	4,128
R^2 (overall)	.047	.057	.031	.037	.064	.106
Mean Dep. variable	.771	.642	.731	.771	.805	.817
CNAE industry panels	532	519	500	472	411	317
Cohort panels	6	5	4	3	2	1

Source: RAIS 1995-2001, employee spinoff firms with at least one non-team member at time of entry.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in HMR. Two observations per employee spinoff firm, one for team members and one for non-team workers. Different *CNAE* from parent is only defined for those spinoff firms having (i) a non-missing mode *CNAE*, (ii) a surviving parent firm at birth t, and (iii) a parent firm with non-missing mode *CNAE*. Robust standard errors in parentheses: * significance at ten, ** five, *** one percent.

likelihood of such mistakes is greater, the more different is the new enterprise from its parent. Our control variables are indicators for four-digit *CNAE* industry and firm birth cohort (1995-2000).

Focusing on the second column of Table 1, we see that for workers hired at startup who have remained with a spinoff firm in the same industry as its parent for one year, the proportion of team members that remains for a second year is 11.7 percentage points greater than the proportion of non-team workers that remains for a second year. This difference declines monotonically with worker tenure from a firm's second year through its sixth year of existence. The sample mean of the dependent variable, in contrast, steadily increases from the second through sixth year so the retention hazard of non-team workers must increase over time. These results are strongly supportive of Proposition 1, except for the increase in the retention hazard gap from the first to the second year of employment. This increase is driven by the fall in the retention hazard rate for non-team workers (note the fall in the sample mean of the dependent variable), so it appears that the failure of Lemma 1 (and consequently Lemma 2) to hold between the first and second years is the underlying cause of this only failure of Proposition 1. This pattern is consistent with the well-known tendency for separation hazard rates to rise at the very beginning of employment before falling (e.g. Farber 1999).[20]

[20]The ability to predict an initial rise in the separation hazard is the only empirically substantive loss resulting from our simplification of the employer learning model of Jovanovic (1979). Farber (1999, pp. 2463-2464) provides a good intuitive explanation: "a worker might stay despite some early signals of poor match quality because there remains a relatively high probability that match quality will turn out to be high. Over time, the reservation match quality increases as the variance of the updated beliefs about match quality falls and the option value decreases. At this point,

The number of observations in Table 1 decreases sharply as we progress from $t+1$ to $t+6$. This occurs for three reasons. First, for each additional year over which we measure retention, we lose a cohort of firms. Second, within any cohort the cumulative number of firm exits increases with time.[21] Third, even if a firm survives it may lose all its team members, all its other startup workers, or both.

Cumulatively, after five years team members are 60 percent more likely than non-team members to remain with a spinoff firm in the same industry as its parent. This is computed by replacing the proportions of workers that survive from one year to the next with the proportions of workers hired at founding that survive as the dependent variable in Table 1, and taking the ratio of the coefficient on the team indicator to the mean of the dependent variable for non-team workers in the $t+5$ column.

Turning to Proposition 2, we see that the coefficient on the interaction between the different industry indicator and the team indicator is always negative and is statistically significant from $t+1$ to $t+4$, which strongly supports the prediction that greater hiring error will reduce the retention hazard gap between team members and non-team workers. Proposition 2 also predicts that this reduction should decrease (in absolute value) with worker tenure. The coefficient on the interaction in Table 1 does decrease in absolute value after the second year of employment, but the decrease is not monotonic. The increase in the absolute value of the coefficient from the first to the second year is consistent with the already-noted failure of Lemma 1 to hold between the first and second years.

Empirically, workers differ in many characteristics that may influence their retention rates. We will use the same set of control variables that were included in log wage regressions by Menezes-Filho et al. (2008) in their work with the RAIS data cited above. They included education categories, a quartic in potential experience (age minus education), occupational categories, gender, and the interactions of gender with all of the other controls. The only difference is that we will use occupations at workers' previous employers, because sorting of workers into their current occupations is arguably endogenous to their match qualities at the spinoff firms.[22] The previous employers of team members were parent firms, but non-team workers cannot necessarily be tracked to previous formal sector employment. We therefore distinguish between all non-team workers and trackable non-team workers. Note that trackable non-team workers and team members are all equally "movers" in the sense of having left previous formal sector employment.

For some jobs there are specialized skills not everyone can acquire, such as operating a certain machine tool or programming a certain computer language. A spinoff firm may need the same set of specialized skills as its parent, and it may be hard to find applicants with these skills besides those employees the spinoff can attract from the parent. This would not be captured by the control variables listed so far, yet these workers might have unusually high survival rates at the spinoff firms. We will therefore add log wage at previous employer as a control. Workers with rare skills that are transferable to other firms should earn higher wages at their previous employers.

Table 2 reports the mean values of the control characteristics for team members, trackable non-team workers, and all non-team workers. We see that team members have more education and

separation rates increase."

[21] We remove any exiting firm from our sample in its first year of exit, since otherwise the proportion of surviving employees would be computed to be zero for both team and non-team members for that firm in that year.

[22] Using current occupations at the spinoff firms leaves our results virtually unchanged.

Table 2: MEANS OF WORKER CHARACTERISTICS AT SPINOFF, TEAM VS. NON-TEAM

	Employees in		
	Team	Nonteam trackable	Nonteam all
	(1)	(2)	(3)
Pot. labor force experience	20.076	18.528	16.638
	(.011)	(.014)	(.012)
Middle School or less	.624	.654	.655
	(.0005)	(.0006)	(.0005)
Some High School	.274	.259	.269
	(.0005)	(.0006)	(.0005)
Some College	.030	.027	.026
	(.0002)	(.0002)	(.0002)
College Degree	.072	.060	.050
	(.0003)	(.0003)	(.0002)
Prev. Prof. or Manag'l. Occ.	.132	.099	
	(.0003)	(.0004)	
Prev. Tech'l. or Superv. Occ.	.175	.177	
	(.0004)	(.0005)	
Prev. Unskilled Wh. Collar Occ.	.161	.169	
	(.0004)	(.0005)	
Prev. Skilled Bl. Collar Occ.	.400	.404	
	(.0005)	(.0006)	
Prev. Unskilled Bl. Collar Occ.	.131	.152	
	(.0003)	(.0005)	
Prev. Monthly wage	5.734	5.541	
	(.0009)	(.001)	
Female employee	.293	.269	.302
	(.0005)	(.0006)	(.0005)
Obs.	983,833	607,075	848,932

Source: RAIS 1995-2001, workers at employee spinoff firms.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in HMR. Potential labor force experience equals age minus years of education. Previous occupations and wages are those at last employer. Missing data for education: Team 3,378, trackable non-team 2,414, all non-team 3,677. Missing data for potential experience: Team 4,244, trackable non-team 3,055, all non-team 4,981. Missing data for previous occupation: Team 20,140, trackable non-team 21,921. Missing data for previous wage: Team 12,394, trackable non-team 13,153. Standard errors in parentheses.

more potential experience than trackable non-team workers or all non-team workers. Restricting the sample of non-team workers to trackable workers raises average education and average potential experience and lowers the female share, as one would expect. Team members are also more likely than trackable non-team workers to have held professional or managerial positions at their previous employers, and they received higher wages at their previous employers. It is certainly plausible that these differences contribute to the positive retention hazard gap between team members and non-team workers in Table 1, though not necessarily to the other predictions in Propositions 1 and 2.[23]

Tables 3 and 4 repeat the retention hazard regressions of Table 1 at the individual level. Table 3 considers the full worker sample, Table 4 restricts the sample to trackable non-team workers for comparability. The dependent variable equals one if a worker remains employed at the spinoff firm from one year to the next and zero otherwise. Firm-level fixed effects are included and standard errors are clustered at the team or non-team level, nested within the firm. We see in both Tables that the lowest education category is usually associated with the lowest retention hazard and that greater potential experience is usually associated with greater retention hazard. When statistically significant, the coefficients for previous occupations other than unskilled blue collar worker are almost always positive. The association of the log of the previous monthly wage with retention hazard is always positive and almost always statistically significant. Despite the importance of these control variables, support for Propositions 1 and 2 remains unchanged, with only marginal decreases in the estimated retention hazard gaps whether all non-team workers or only trackable non-team workers are included.[24]

Insofar as scarcity of workers with relevant skills acquired on the job is not captured by their wages at their former employers, we can to try to control for labor market thickness directly. We computed the number of workers in the birth year of the spinoff firm who are in the same municipality and same industry as a proxy for local labor-market thickness. We added the interaction of the log of this number with the team member indicator to the explanatory variables in Tables 3 and 4. If the retention hazard gap between team members and non-team workers is driven by the inability of the partners to find non-team workers with relevant on-the-job skills, the coefficient on the interaction term should be negative. We find that this coefficient is negative and statistically significant only in the first year of employment and statistically insignificant (usually positive) thereafter (table not shown). In group-level regressions one can identify the direct effect on the retention hazard of the log of the number of workers in the same municipality and same industry as the spinoff firm, and it is typically negative and statistically significant. In other words, separations are more frequent in municipalities or sectors with large local employment. We interpret this finding to mean that our proxy is a good measure of labor market thickness.

We turn at last to empirical evaluation of the alternative hypothesis that team members have innately high ability rather than high match quality for their new spinoff employers. Under this alternative, the spinoff partners use their social networks to identify high ability workers at the parent firms, and are able to bid these workers away because their new firms are more productive than the parent firms. Though it may seem that including the log wage at the previous employer

[23] An additional concern is that more non-team workers might work part time. In fact, average hours worked per week by team members and non-team workers are virtually identical (very slightly higher for non-team workers.)

[24] This statement continues to hold even if we replace the six occupational categories with a full set of 350 occupation dummies.

Table 3: RETENTION HAZARD GAP AT SPINOFF CONTROLLING FOR WORKER CHARACTERISTICS

	All workers					
Retention indicator	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Team member	.073	.112	.066	.045	.032	.028
	(.002)***	(.004)***	(.003)***	(.004)***	(.007)***	(.008)***
Team memb. × Diff. *CNAE*	-.0005	-.016	-.013	-.006	.002	-.017
	(.005)	(.004)***	(.004)***	(.005)	(.009)	(.011)
Some High School	.024	.032	.025	.016	.015	-.003
	(.003)***	(.005)***	(.005)***	(.005)***	(.007)**	(.011)
Some College	.019	.016	.012	.003	-.008	.040
	(.005)***	(.007)**	(.007)*	(.009)	(.013)	(.037)
College Degree	.018	.017	.008	-.005	-.006	.0009
	(.004)***	(.006)***	(.007)	(.009)	(.011)	(.019)
Pot. lab. force exp.	-.005	.0005	.006	.008	.006	.003
	(.0009)***	(.002)	(.002)***	(.002)***	(.003)*	(.004)
Sq. Pot. lab. force exp.	.0003	.0002	-.0002	-.0003	-.0003	.0001
	(.00006)***	(.0001)*	(.0001)	(.0001)*	(.0002)	(.0003)
Cub. Pot. lab. force exp.	-6.79e-06	-5.51e-06	3.22e-06	3.36e-06	5.13e-06	-7.24e-06
	(1.34e-06)***	(2.30e-06)**	(2.92e-06)	(3.76e-06)	(5.71e-06)	(7.18e-06)
Qrt. Pot. lab. force exp.	4.87e-08	4.70e-08	-2.64e-08	-1.93e-08	-4.46e-08	7.48e-08
	(1.12e-08)***	(1.82e-08)***	(2.41e-08)	(3.25e-08)	(4.80e-08)	(6.11e-08)
Female employee	-.011	-.001	.001	-.004	-.019	.009
	(.006)*	(.010)	(.011)	(.016)	(.024)	(.036)
Obs.	1,227,783	666,338	300,647	133,370	54,948	20,518
R^2	.253	.236	.237	.256	.271	.280
Mean Dep. variable	.762	.665	.753	.791	.817	.808
Firm panels	60,182	41,295	23,142	12,368	5,544	2,040

Source: RAIS 1995-2001, employee spinoff firms with at least one non-team member at time of entry.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in HMR. Coefficients for interactions of female with all other worker characteristics are not shown. Different *CNAE* from parent is only defined for those spinoff firms having (i) a non-missing mode *CNAE*, (ii) a surviving parent firm at birth t, and (iii) a parent firm with non-missing mode *CNAE*. Omitted category for education is primary school or less. Clustered standard errors at the level of teams in parentheses: * significance at ten, ** five, *** one percent.

Table 4: RETENTION HAZARD GAP AT SPINOFF CONTROLLING FOR WORKER CHARACTERISTICS, TRACKABLE WORKERS ONLY

	Trackable workers					
Retention indicator	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Team member	.068	.108	.062	.045	.027	.020
	(.002)***	(.004)***	(.003)***	(.004)***	(.009)***	(.010)**
Team memb. × Diff. *CNAE*	.0009	-.016	-.010	-.011	.002	-.013
	(.005)	(.005)***	(.005)**	(.006)*	(.011)	(.014)
Some High School	.019	.028	.022	.010	.009	-.016
	(.004)***	(.005)***	(.006)***	(.005)**	(.008)	(.013)
Some College	.010	.010	.007	-.006	-.020	.029
	(.005)*	(.007)	(.008)	(.010)	(.014)	(.039)
College Degree	.0006	.002	.002	-.020	-.017	-.025
	(.005)	(.005)	(.009)	(.010)**	(.012)	(.019)
Pot. lab. force exp.	-.002	.004	.009	.009	.007	.004
	(.001)*	(.002)**	(.002)***	(.003)***	(.004)*	(.005)
Sq. Pot. lab. force exp.	.0002	-.00002	-.0004	-.0003	-.0004	.00004
	(.00007)**	(.0001)	(.0001)**	(.0002)*	(.0003)	(.0003)
Cub. Pot. lab. force exp.	-3.97e-06	-1.81e-06	7.34e-06	5.02e-06	8.73e-06	-5.65e-06
	(1.64e-06)**	(2.79e-06)	(3.54e-06)**	(4.53e-06)	(6.72e-06)	(8.12e-06)
Qrt. Pot. lab. force exp.	3.10e-08	2.23e-08	-5.93e-08	-3.12e-08	-7.56e-08	6.29e-08
	(1.31e-08)**	(2.13e-08)	(2.86e-08)**	(3.83e-08)	(5.57e-08)	(6.87e-08)
Prev. Prof./Manag'l. Occ.	.020	.022	-.010	.005	-.004	.013
	(.005)***	(.010)**	(.006)*	(.008)	(.009)	(.018)
Prev. Tech'l./Superv. Occ.	.020	.019	.002	.002	.004	-.006
	(.004)***	(.008)**	(.005)	(.008)	(.011)	(.020)
Prev. Unsk. Wh. Coll. Occ.	.009	.005	-.003	.005	.00002	-.003
	(.003)***	(.007)	(.006)	(.007)	(.011)	(.016)
Prev. Skld. Bl. Collar Occ.	.014	.012	-.001	-.0007	-.003	-.014
	(.006)**	(.008)	(.006)	(.006)	(.009)	(.013)
Prev. Monthly wage	.011	.011	.009	.007	.008	.009
	(.002)***	(.003)***	(.003)***	(.003)***	(.004)**	(.007)
Female employee	.031	.058	.027	.002	-.003	.062
	(.014)**	(.031)*	(.025)	(.029)	(.046)	(.076)
Obs.	1,016,190	552,884	250,797	110,520	45,371	16,823
R^2	.260	.244	.242	.261	.276	.288
Mean Dep. variable	.773	.677	.759	.797	.821	.806
Firm panels	57,107	38,035	20,233	10,543	4,691	1,723

Source: RAIS 1995-2001, employee spinoff firms with at least one non-team member at time of entry.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in HMR. Coefficients for interactions of female with all other worker characteristics not shown. Different *CNAE* from parent only defined for those spinoff firms having (i) a non-missing mode *CNAE*, (ii) a surviving parent firm at birth t, and (iii) a parent firm with non-missing mode *CNAE*. Omitted category for education is primary school or less. Omitted category for occupation is unskilled blue collar. Occupation and wage data are for worker's last employment spell (lasting at least three months) before joining the spinoff. Clustered standard errors at the level of teams in parentheses: * significance at ten, ** five, *** one percent.

in our retention hazard regressions controls for this possibility, it could be that the team members were not recognized by the parent firms as having high ability.[25] In this case the alternative hypothesis comes close to being only a reinterpretation of our model, but we can distinguish it if we can observe productivity of spinoff firms relative to their parents, since under the alternative hypothesis higher relative productivity will be associated with higher unobserved ability of team members and a higher retention hazard gap.

The RAIS data set does not cover output, so we use relative firm size as a proxy for relative productivity. We measure spinoff firm size by log employment at birth, but parent firm size by log employment in the year prior to birth of the spinoff since parent employment in the year of spinoff birth is reduced by the number of team members. We also restrict our sample to spinoffs born from parents that survive through 2001, the last year in our data, because relative spinoff productivity should be a less important factor in attracting high ability workers from dying parents.

Table 5 reports the regressions in Table 4 for the restricted sample, adding an interaction of the team indicator with the log of the ratio of spinoff employment at birth to parent employment in the preceding year (the direct effect of this new variable is absorbed by the firm fixed effect). We see that this coefficient is positive and significant for the first two years of employment and positive for three of the remaining four years, offering some support for the hypothesis that more productive spinoff firms are able to recruit workers with innately higher ability from their parents.[26] However, the coefficients on the team indicators are reduced only slightly by taking into account the interactions with relative firm size, so this hypothesis is better seen as a supplement to our theory than an alternative.[27]

In summary, comparing retention hazards at spinoff firms between founding team workers and non-team workers strongly supports the predictions of our social capital model. Conditional on worker characteristics and firm effects, team members are significantly more likely to retain their spinoff employment in early years and this gap in retention hazards decays over time. The gap in retention hazards is smaller for spinoffs of parents in different industries, consistent with the model prediction that hiring errors reduce the importance of social capital and the interpretation that hiring errors are more frequent at cross-industry spinoffs. We now turn to complementary evidence from separation hazards and worker tenure at parent firms.

5 Departure Hazards and Worker Tenure at Parents

In this section we investigate aspects of our model regarding the parent-firm tenure of workers who depart for a spinoff versus those workers who do not. Our model predicts that the spinoff firm will be unable to recruit workers of known match quality with the parent. The longer workers have been with the parent, the more likely is their match quality to be known to the parent. Concretely,

[25]The fact that recruitment by spinoffs reveals these workers' high abilities to the parent firms does not affect the wages we observe for them at the parents.

[26]Using all workers instead of trackable workers does not qualitatively change our results.

[27]In our model, spinoff productivity and size equal parent productivity and size by assumption. In Table 5, the mean of the log size ratio for the different years fluctuates between -1.4 and -1.9, indicating that spinoff firms are typically one-seventh to one-quarter as large as their parents. Adding the coefficients on the interaction terms times the mean log size ratios to the coefficients on the team indicators yields 0.055, 0.097, 0.057, 0.049, 0.030, and 0.006 for $t+1$ through $t+6$, respectively.

Table 5: RETENTION HAZARD GAP, PARENTS SURVIVING TO 2001 ONLY

	All workers					
Share of retained workers	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Team member	.085	.119	.068	.047	.032	.028
	(.003)***	(.004)***	(.003)***	(.004)***	(.008)***	(.009)***
Team memb. × Diff. *CNAE*	.007	-.011	-.010	-.002	-.0005	-.012
	(.005)	(.005)**	(.004)**	(.006)	(.008)	(.011)
Team mmb. × Dff. Log empl.	.015	.009	.004	.004	-.002	.002
	(.001)***	(.001)***	(.0009)***	(.001)***	(.002)	(.003)
Some High School	.024	.032	.025	.016	.017	-.003
	(.003)***	(.006)***	(.005)***	(.005)***	(.007)**	(.012)
Some College	.018	.014	.012	.004	-.013	.044
	(.005)***	(.007)*	(.007)*	(.010)	(.014)	(.038)
College Degree	.016	.017	.008	-.007	-.014	.004
	(.004)***	(.006)***	(.007)	(.009)	(.011)	(.020)
Pot. lab. force exp.	-.005	.0009	.006	.008	.006	.004
	(.0009)***	(.002)	(.002)***	(.002)***	(.004)*	(.004)
Sq. Pot. lab. force exp.	.0003	.0001	-.0002	-.0002	-.0003	.0001
	(.00006)***	(.0001)	(.0001)	(.0002)	(.0002)	(.0003)
Ctc. Pot. lab. force exp.	-6.65e-06	-5.06e-06	2.79e-06	3.15e-06	5.58e-06	-7.29e-06
	(1.36e-06)***	(2.38e-06)**	(2.98e-06)	(3.84e-06)	(5.90e-06)	(7.33e-06)
Qrt. Pot. lab. force exp.	4.77e-08	4.37e-08	-2.23e-08	-1.78e-08	-4.92e-08	7.51e-08
	(1.13e-08)***	(1.90e-08)**	(2.45e-08)	(3.30e-08)	(4.93e-08)	(6.23e-08)
Female employee	-.012	.002	-.002	-.002	-.018	.020
	(.006)*	(.010)	(.012)	(.016)	(.025)	(.037)
Obs.	1,181,160	639,871	291,435	12,8848	52,507	19,852
R^2	.252	.232	.236	.257	.269	.281
Mean Dep. variable	.762	.666	.753	.791	.817	.807
Firm panels	57,686	39,691	22,313	11,946	5,355	1,941

Source: RAIS 1995-2001, employee spinoff firms with at least one non-team member at time of entry and parent firm that survives to 2001. Trackable employees only.

Notes: Definition of employee spinoff (quarter-workforce criterion) as described in HMR. Coefficients for interactions of female with all other worker characteristics are not shown. Different *CNAE* from parent is only defined for those spinoff firms having (i) a non-missing mode *CNAE*, (ii) a surviving parent firm at birth t, and (iii) a parent firm with non-missing mode *CNAE*. Difference in log employment is for spinoff in birth year and parent in previous year. Omitted category for education is primary school or less. Clustered standard errors at the level of teams in parentheses: * significance at ten, ** five, *** one percent.

the rate at which workers depart from the parent to a spinoff, where they become founding team members, is

$$\dot{T}_i(\tau)/S_i(\tau) \equiv \theta(1-\gamma)\alpha\, p_0 \cdot q_i(\tau),$$

where $q_i(\tau)$ denotes the fraction of workers whose match quality is unknown in a given worker cohort $S_i(\tau)$ with tenure τ at parent firm i.[28] We call this a parent worker's *departure hazard* to join a spinoff. The departure hazard depends on the network extent α. In contrast, parent workers separate for unemployment (or employment at a firm that is not their parent's spinoff) at the conventional *separation rate* $\dot{U}_i(\tau)/S_i(\tau) \equiv \delta + \phi(1-p_0)\, q_i(\tau)$, which is independent of α.

As explained in subsection 2.1, our general-equilibrium model omits the time required for the potential spinoff entrepreneurs to learn the prospective match quality of their colleagues at the spinoff firm. In other words, we assume in the general-equilibrium version of our model that networks of size α arise instantaneously. Network formation may take time in practice. Realistically, a worker's network size should depend on the worker's prior job history at the parent and therefore the worker's tenure at parent firm i. In this spirit, we can allow for the possibility that a parent worker's network extent $\alpha_i(\tau)$ is a function of tenure and satisfies $\dot{\alpha}_i(\tau) > 0$. With increasing tenure at the parent firm, workers will meet more potential entrepreneurs in the workplace and at the coffee pots for "cafezinhos" (small cups of black coffee)—the Brazilian social equivalent to the U.S. water cooler.

Proposition 3. *The departure hazard of workers who join an employee spinoff's founding team strictly increases in tenure at low levels of parent-firm tenure and strictly decreases at high levels of parent-firm tenure if and only if* $\dot{\alpha}_i(0)/\alpha_i(0) > -\dot{q}_i(0)/q_i(0)$ *and* $\dot{\alpha}_i(\hat{\tau})/\alpha_i(\hat{\tau}) < -\dot{q}_i(\hat{\tau})/q_i(\hat{\tau})$ *for some finite tenure* $\hat{\tau}$.

Proof. The departure hazard of workers who join a founding spinoff team is $\dot{T}_i(\tau)/S_i(\tau) \equiv \theta(1-\gamma)\alpha p_0 q_i(\tau)$. By this definition, $\partial[\dot{T}_i(\tau)/S_i(\tau)]/\partial\tau > 0$ if and only if $\dot{\alpha}_i(\tau)/\alpha_i(\tau) > -\dot{q}_i(\tau)/q_i(\tau)$, which is strictly positive by Lemma 2. □

Under the condition of the proposition, at some point learning within social networks becomes slow while learning by employers continues fast. The empirical prediction is that we should see a plot of the probability of leaving the parent for the spinoff firm against worker tenure to follow an inverted U. The right arm of the inverted U becomes steeper, not flatter, because the fraction of cohort employees with unknown match quality declines with tenure at an accelerating rate (Lemma 2).[29] The low departure hazards for parent employees with long tenure are a prediction of our model because workers with high tenure are more likely to be of known quality to the parent. Low departure hazards at short tenure follow if it takes time for parent employees to become members of a social network.

Proposition 4. *The separation hazard of workers who become unemployed strictly declines in tenure at any level of parent-firm tenure.*

[28] In addition, parent workers become partners at the spinoff at a constant rate $\theta\gamma$. Partners are not reported in the RAIS employment records at the spinoff so we restrict our empirical attention to founding team members.

[29] By Lemma 2, an example of a sufficient condition for this inverted U shape is that $\dot{\alpha}_i(0) > [\theta(1-\gamma)\alpha_i(0)^2 p_0 + \phi]$ and that $\dot{\alpha}_i(\hat{\tau}) < \phi p_0 \alpha_i(\hat{\tau})$ for some finite tenure $\hat{\tau}$.

Proof. The hazard of a worker transition to unemployment is $\dot{U}_i(\tau)/S_i(\tau) \equiv \delta + \phi(1-p_0)\, q_i(\tau)$, which strictly declines because $\dot{q}_i(\tau)/q_i(\tau) < 0$ by Lemma 2. □

Our model of mobilizing social capital is not needed to make the prediction that an employee with long tenure will be unlikely to separate from the employer. Indeed, we expect that separation to another, non-spinoff employer or to unemployment should also diminish with long tenure. Thus it is at short tenure that we expect to see a difference between separation to spinoffs and other separations. We examine all three types of separation below.

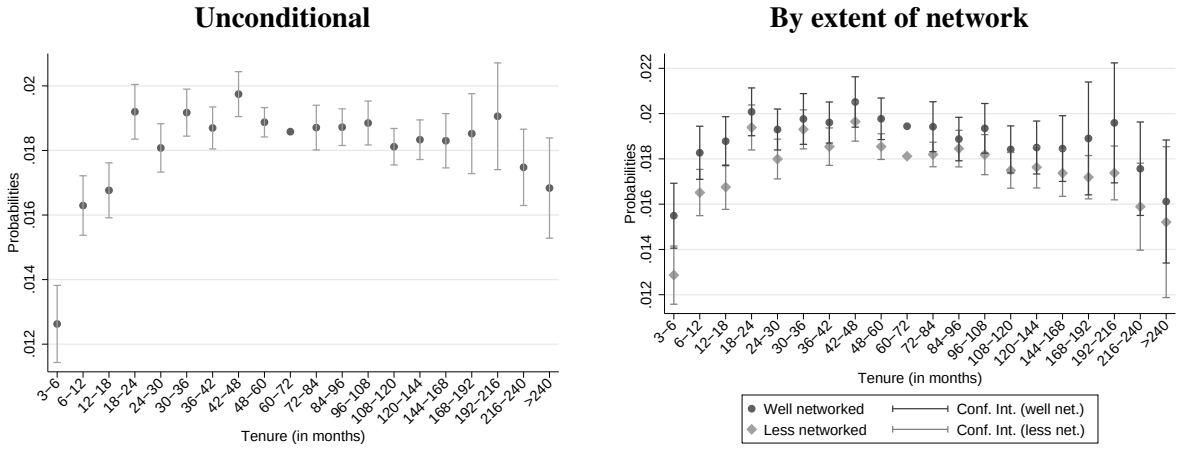
When comparing tenure at a parent firm between workers who join a spinoff and workers who remain at the parent, we must be careful to identify the correct choice set facing the entrepreneurs who are recruiting the workers. This consideration leads us to define the dependent variable for separation to spinoff as equal to one if a worker at a parent firm joins a spinoff born in the following year and zero otherwise. We do not use the current year because if a spinoff firm is born early in a year, there is a risk that team members will not have been recorded as having worked for the parent in that year, and a risk that workers who did not join the spinoff but are recorded as having worked for the parent in that year were not at the parent when the spinoff was born. Our dependent variable definition also implies that employees whose last employment at the parent was two or more years before spinoff birth are not included in our sample, even if there are team members among them. We feel that for this minority of cases it is more accurate to think of the team members as having been hired out of unemployment, self employment or the informal sector so that tenure at the parent is irrelevant.[30]

Recall that in Table 5 we restricted our spinoff sample to those spinoffs whose parents survive until 2001, the end of our sample period. This is also the sample of parents we want to use in our tenure analysis, since workers may want to separate from a dying parent regardless of match quality.[31]

We do not want to impose a functional form on the relationship between departure hazards and tenure, so we place observed tenure into twenty bins designed to contain similar numbers of observations. This means that the length of the tenure intervals for the twenty bins increases with tenure. In the sample of parent workers, we then regress an indicator for a worker's departure to a spinoff born the following year (or an indicator for a worker's transition to another job or unemployment) on dummies for nineteen of these tenure bins, omitting the midpoint bin for 60-72 months of tenure. In the regressions, we include a full set of worker controls (experience, education, occupation, gender, log wage, and gender interactions as in Tables 3 through 5), and condition on parent-year fixed effects. We cluster the standard errors at the parent-year level. To facilitate interpretation, we plot the coefficient estimates for the nineteen tenure-bin dummies, adding these estimates to the predicted probability from all other regressors (including the constant which reflects the omitted tenure bin coefficient of 60 to 72 months). Since we are interested in

[30] In other words, the assumption of our model that workers exit firm social networks when they separate from the firms is an oversimplification. Unemployed members of the social networks of spinoff entrepreneurs will accept their job offers if the parties know (subject to hiring error) that the workers are of high match quality with the planned firms, but not if they know they are of low match quality.

[31] All workers with less than three months of tenure at the parent are dropped from the sample. Recall from Section 3 that when HMR identified employee spinoff firms and their parents they used the criterion that if at least one quarter of the founding workers at a new firm previously worked for the same existing firm, the new firm is an employee spinoff and the existing firm is its parent. Previous work was defined as a job spell of at least three months.



Source: RAIS 1995-2001, parent firms (of employee spinoffs) that have employee spinoff in subsequent year and that survive to 2001.
Notes: Definition of parent firm and employee spinoff (quarter-workforce criterion) as described in HMR. Sample includes workers who continue at parent, separate for other RAIS employment or unemployment, or depart to join spinoff, but excludes retirements and deaths. Probability estimates from parent-year fixed effects regression of the departure hazard on the set of tenure bin indicators, conditional on worker characteristics as in Table 3, the log monthly wage and a constant. Interactions of tenure bin indicators with an indicator for being well networked (at least two preceding occupations at employer), in right graph. Estimated probabilities are tenure-bin coefficients plus the predicted value from remaining regressors (including constant for omitted tenure bin coefficient of 60 to 72 months). Confidence intervals (95% significance) from clustered standard errors at the parent-year level by tenure-bin indicator, relative to omitted tenure bin.

Figure 1: **Departure Hazards of Parent Workers to Spinoffs**

testing the tenure-bin coefficients against each other, we compute the confidence intervals (at the 95-percent significance level) around each tenure-bin coefficient using the individual tenure bin's standard error, excluding the standard-error contribution of the predicted probability from all other regressors.

The left-hand graph in Figure 1 depicts the tenure bin results for the departure hazard regression. The predicted departure hazard of a parent worker to a spinoff firm is significantly lower at initial tenure levels up to 18 months, compared to the midpoint tenure bin (with 60 to 72 months). At long tenure of 216 and more months, the predicted departure hazard of a parent worker to a spinoff firm is again significantly lower than the midpoint tenure bin and its neighboring bins. This overall shape resembles the inverted U expected from Proposition 3.

Our theoretical rationale for the increasing left arm of the inverted U is that employees with short tenure have smaller networks so that their prospective match quality with a spinoff is not yet known to many potential entrepreneurs. An alternative explanation might be that, in general, outside learning is faster than employer learning at short tenure. Below we will turn to evidence on parent employees who separate to work for a third firm (Figure 2). In contradiction to the alternative explanation, we will find that a parent employee's transition rate to other firms strictly drops with tenure for employees of any tenure.

To shed more direct evidence on our explanation that short-tenured employees have smaller networks, we distinguish between parent workers who have held more than one occupation during

their tenure at the parent and workers who have held only one occupation (out of 350 recorded occupations).[32] The number of occupation changes at the parent is a proxy to an employee's membership in social networks at the parent under the assumption that multiple occupation changes expose an employee to several potential spinoff entrepreneurs and therefore permit entry into several social networks. We consider employees with at least one occupation change at the parent as relatively well networked. In our parent-firm sample, 29.2 percent of workers have held more than one occupation at their employer. Since these occupation changes also allow the parent to learn more about the employee's general skills and human capital, by exposing the employee to different on-the-job tests that provide additional information, we can use the proxy to distinguish our hypothesis of social capital formation from an explanation based on transferrable human capital. Our theory predicts that well networked workers with many occupation changes (and relatively high α_i) should more frequently depart from parents to spinoffs, whereas the alternative hypothesis predicts the opposite.

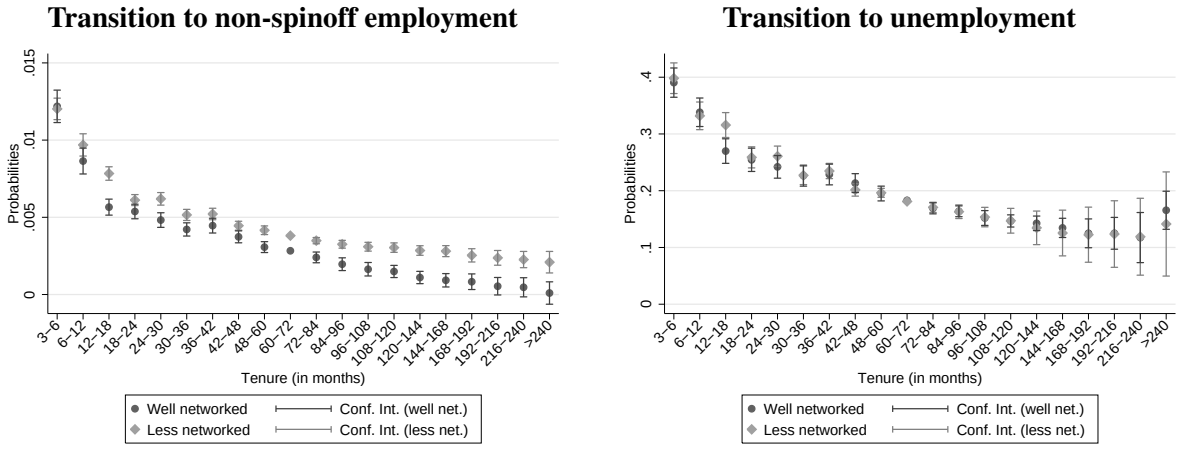
The right-hand graph in Figure 1 depicts the tenure bin results for both well networked employees with at least one occupation change (*well networked employees*) and employees with no occupation change at their current employer (*less networked employees*). In line with our social-capital explanation, well networked employees exhibit consistently higher hazards of departure to a spinoff at all tenure levels without exception, though not statistically significantly higher rates. Strikingly, the difference in departure hazards is strongest in the left arm of the inverted U. Short-tenured employees with a background of at least one occupation change at the parent are more likely to depart to a spinoff than short-tenured employees with no occupation change at the parent. If the reason for increasing departure rates of short-tenured employees were transferrable human capital, about which parents learn more from occupation switches, then short-tenured employees with a multiple-occupation background should be retained more frequently and depart at lower rates. The opposite is the case. Consistent with social-capital accumulation, the flatter left arm suggests that well networked employees are similar to longer-tenure employees from an early tenure stage on.

We now turn to Proposition 4. The left-hand graph in Figure 2 shows the separation hazard of parent-firm workers with a job-to-job transition to another formal-sector firm.[33] This separation hazard strictly declines with parent-firm tenure, just as Proposition 4 predicts. Revisiting our distinction between well networked multi-occupation employees and less networked single-occupation employees in the left-hand graph in Figure 2, the job-to-job transition hazard of well networked employees is strictly and statistically significantly lower than the transition rate of less networked employees. In a model of firm-specific human capital, in which all worker skills are general but firms demand skills in differently weighted combinations (Lazear 2003), one would expect multi-occupation employees to offer a broader skill set so that they would appeal to more outside employers and arguably exhibit higher, not lower, job-to-job transition hazards. We take this evidence as indicative that our multi-occupation indicator is a good proxy to a worker's social network.

The right-hand graph in Figure 2 shows the separation hazard of parent-firm workers who

[32] In our version of RAIS, occupations are reported at the CBO (*Classificação Brasileira de Ocupações*) 3-digit level which classifies occupations into 350 categories.

[33] Excluding parent workers who depart to a spinoff.



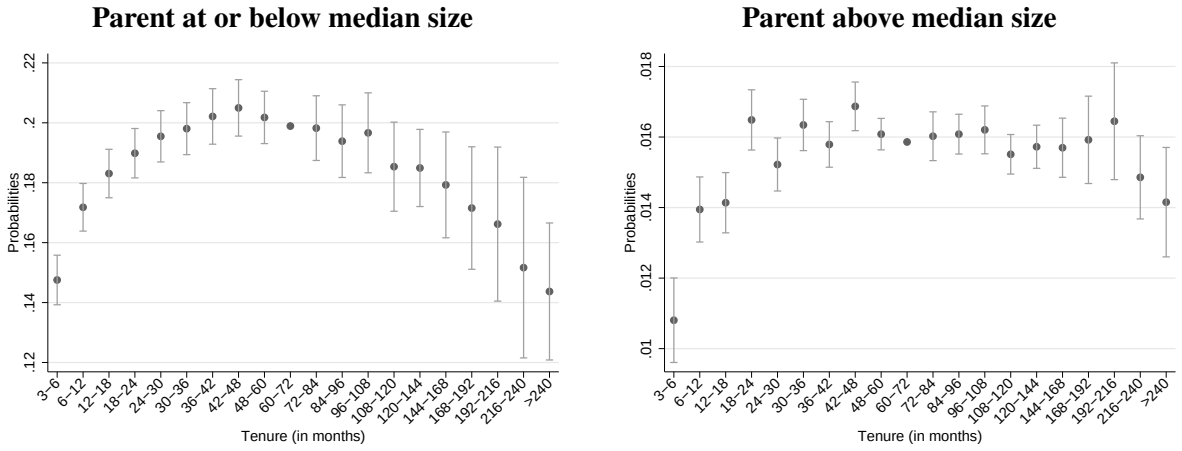
Source: RAIS 1995-2001, parent firms (of employee spinoffs) that have employee spinoff in subsequent year and that survive to 2001.
Notes: Definition of parent firm (quarter-workforce employee spinoff criterion) as described in HMR. Unemployment can include self employment and informal work. Sample restricted to workers who continue at parent or separate for other RAIS employment (left graph) or no recorded RAIS employment (right graph), excluding workers joining spinoffs and excluding retirements and deaths. Probability estimates from parent-year fixed effects regression of the departure hazard on the set of tenure bin indicators, conditional on worker characteristics as in Table 3, the log monthly wage and a constant. Interactions of tenure bin indicators with an indicator for being well networked (at least two preceding occupations at employer). Estimated probabilities are tenure-bin coefficients plus the predicted value from remaining regressors (including constant for omitted tenure bin coefficient of 60 to 72 months). Confidence intervals (95% significance) from clustered standard errors at the parent-year level by tenure-bin indicator, relative to omitted tenure bin.

Figure 2: **Separation Hazards of Parent Workers to Non-spinoff Employment and Unemployment**

shift to unemployment, self employment or informal work (outside RAIS).[34] This separation hazard strictly declines with parent-firm tenure, just as Proposition 4 predicts, and similarly for both well networked and less networked employees. Somewhat contrary to predictions of the Moscarini (2005) version of the Jovanovic (1979) theory (Lemma 1), and our extended model (Lemma 2), the separation hazards in the left-hand and the right-hand graphs of Figure 2 do not decline at an increasing rate (and the coefficient for the highest tenure bin even rises in the right-hand graph). Since we focus on co-worker learning, and the formation of social capital behind spinoff entrepreneurship, we put this slight inconsistency with employer learning aside.

An interesting feature of the inverted U in Figure 1 is the wide plateau of similar departure hazards for a broad range of intermediate tenure levels. The plateau is consistent with a band of uncertainty where learning by the employer and learning by co-workers in the social network are similarly informative while noise remains. We conjecture that an empirical explanation might be that career opportunities in the internal labor market at the parent firm add noise to the learning processes, an issue we expect to be especially important at large parent firms. A possible explanation is that at large firms workers have more opportunities to change "careers" entirely. With a substantial career change the employer has to restart learning about some of the long-tenured

[34]Excluding parent workers with retirements or deaths, which are recorded in RAIS.



Source: RAIS 1995-2001, parent firms (of employee spinoffs) that have employee spinoff in subsequent year and that survive to 2001.
Notes: Definition of parent firm and employee spinoff (quarter-workforce criterion) as described in HMR. Sample includes workers who continue at parent, separate for other RAIS employment or unemployment, or depart to join spinoff, but excludes retirements and deaths. Probability estimates from parent-year fixed effects regression of the departure hazard on the set of tenure bin indicators, conditional on worker characteristics as in Table 3, the log monthly wage and a constant. Regression samples restricted to parent firms at or below median size (left graph) and above median size (right graph); median parent size is 61 employees. Estimated probabilities are tenure-bin coefficients plus the predicted value from remaining regressors (including constant for omitted tenure bin coefficient of 60 to 72 months). Confidence intervals (95% significance) from clustered standard errors at the parent-year level by tenure-bin indicator, relative to omitted tenure bin.

Figure 3: **Departure Hazards of Parent Workers to Spinoffs**

employees, giving the spinoff a chance to recruit them. Accordingly, we split the sample into parent firms with size at or below median employment (61 employees) and parent firms with size above median employment and repeat the regression behind the left-hand graph in Figure 1 for the two subsamples.

As Figure 3 shows in the left-hand graph, small parent firms exhibit considerably higher departure hazards for spinoffs and a marked inverse U shape with a single peak in coefficient estimates (at 42 to 48 months tenure) and no plateau. In contrast, the right-hand graph for large parent firms shows considerably lower departure hazards and a wide plateau for intermediate tenure levels. This evidence is consistent with the idea that large internal labor markets create uncertainty as to whether co-workers or employers better know workers' relevant match qualities at intermediate tenure levels.

Overall, our results on tenure-related parent-firm departures complement and reconfirm our retention hazard results from the previous section on spinoff workers. The preceding results on spinoff workers showed that knowledge about founding-team members was effective, but prior learning was inferred rather than observed. The parent-firm tenure results offer evidence consistent with the hypothesis that prospective spinoff entrepreneurs learn the match qualities of workers in their networks initially faster than employers learn the same workers' match qualities with their firms.

6 Conclusions

In this paper we have argued that one of the benefits of organizing workers into firms is the creation of social capital that helps successfully match some of these workers to jobs at new firms. There are many other venues where people observe each other "in action," such as schools, military service, and volunteer organizations, and in principle entrepreneurs could also draw on the social capital created there to assemble their founding teams. Recruitment on this basis presumably entails greater hiring error than recruitment based on learning at a parent firm, but the small quantitative effect of hiring error caused by starting a spinoff firm in a different industry than its parent suggests that the benefits might be economically important.

The capabilities and preferences of colleagues by no means exhaust the list of what employees learn inside a parent firm. Industry studies such as Klepper and Sleeper (2005) and Franco and Filson (2006) clearly demonstrate that spinoff firms learn their parents' technologies. Muendler and Rauch (2011) find that exporting spinoffs of exporting parents copy their parents' export destinations and products. By founding a new firm, the employees give us the opportunity to observe what they have learned. As data for spinoffs and their parents become increasingly available, we can expect the study of employee spinoffs to reveal a great deal more about what is learned inside of firms and the value of that learning.

Appendix

A Firm Identifiers

Consistent application of firm identifiers is crucial for our identification of new plants and firms. Plant-level information in RAIS is based on the CNPJ identification number, where CNPJ ('cadastro nacional de pesso juridica') stands for Brazil's national register of legal juristic persons. The first eight digits of CNPJ numbers (CNPJ radical) define the firm and the subsequent six digits the plant/branch within the firm. The CNPJ number is assigned or extinguished, and pertaining register information updated, under legally precisely defined conditions.

The CNPJ number is administered by the Brazilian tax authority Receita Federal, the Brazilian equivalent to the U.S. IRS. In the CNPJ register, Receita Federal maintains information related to the firm's legal form and related matters, which is separately also recorded in RAIS. The following nine types of transactions either trigger the creation or extinction of CNPJ numbers, or updating of the register while maintaining CNPJ numbers. Once extinguished, a CNPJ number cannot be reassigned to any other plant in the future.

1. *Opening a business, becoming a juristic person.* Obtain CNPJ. It is required of any juristic person ('pessoa juridica') in Brazil, a legal entity in Brazilian common and commercial law, to register a CNPJ number with the Receita Federal upon opening a business.[35]

2. *Change in business name ('nome empresarial'), or business sector ('porte da empresa'), or legal form ('*natureza juridica*').* Maintain CNPJ, update register information. Changes from individual entrepreneurs to associations or partnerships of entrepreneurs and owners, or the reverse, do not result in reported changes in legal form.

3. *Change in ownership ('quadro de sócios') at associations and partnerships, or change in management ('administradores'), or change in equity holding at associations and partnerships ('inclusão e alteração de capital social').* Maintain CNPJ, update register information. Note that changes to incorporated firms—juristic persons with independent legal existence such as a limited liability company ('sociedade por quotas de responsabilidade limitada')—are treated differently, see 8 below.

4. *Other changes to the register, including mothballing ('interrupção temporária de atividades') and resumption of operations ('reinício das atividades interrompidas temporariamente'), a change in tax status ('opção ou exclusão do simples', 'qualificação tributária'), a change of responsible physical person (human being) for the CNPJ juristic person ('pessoa física responsável perante o CNPJ'), and several other administrative cases.* Maintain CNPJ, update register information.

5. *Bankruptcy and liquidation.* Maintain CNPJ, update register information. It pertains to the Receita Federal to administer the CNPJ of the extinguished juristic person. Liquidation

[35] There is also a set of legal entities that are not formally juristic persons but are put on equal legal footing with juristic persons by Receita Federal, including real estate condominiums, mutual funds, employer consortia, and foreign consulates.

may be by court order or extrajudicial settlement. The opening and closing of a bankruptcy case must be reported.

6. *Opening new plants/branches.* New plants or branches are registered with the individual CNPJ numbers, where the first eight digits (CNPJ radical) define the firm and the subsequent six digits the plant/branch within the firm.

7. *Partial divestiture/corporate spinout ('cisão parcial').* Maintain CNPJ, update register information. The newly independent firm (divestiture or spinout) receives an own CNPJ. In practice, a partial divestiture might coincide with the acquisition of an individual plant by another firm.

8. *Merger of firm with other firm ('fusão'), acquisition of firm by other firm ('incorporação') or complete divestiture/corporate spinout into newly independent firms ('cisão total').* Extinguish CNPJ of firm that undergoes change. In the case of mergers and complete divestitures, the newly independent firm(s) obtain CNPJ(s) of their own. In the case of a plant acquisition, if the divested plant is not incorporated as a firm, the acquiring firm's CNPJ radical is retained and six new digits for the new plant are added. Note that the above applies to the acquisition of the firm as a whole, not select plants within the firm (for those cases see 7).

9. *Inactivity since day of foundation ('empresa que não iniciou atividades (inativa desde a abertura)').* Extinguish CNPJ.

Important for employee spinoffs, a change in ownership at associations or partnerships does not result in a change in CNPJ, as explained under item 3. Divestitures include both management-initiated offspring that become standalone firms (corporate spinouts or complete splitups ('cisão total')) and management-initiated offspring from parent firms' M&A activity (such as a merger ('fusão'), an acquisition ('incorporação'), and a partial splitup ('cisão parcial')). These are covered under items 7 and 8.

B Solutions of Value Functions

To solve the system of four equations (6) through (9) in the four unknown value functions, conditional on the job finding rate λ, define the constants $c_1 \equiv [\phi + \theta(1-\gamma)\alpha(1-\bar{\varepsilon})]p_0$, $c_2 \equiv \theta\gamma$, $c_3 \equiv \delta + \theta + \phi(1-p_0)$ and $c_4 \equiv (\delta + \theta)$ for brevity so that

$$\begin{aligned} U &= \frac{b + \lambda V(p_0)}{r + \lambda}, \\ V(p_0) &= \frac{w(p_0) + c_1 V(1) + c_2 P + c_3 U}{r + c_1 + c_2 + c_3}, \\ V(1) &= \frac{\mu_H + c_2 P + c_4 U}{r + c_2 + c_4}, \\ P &= \frac{a + \theta U}{r + \theta}. \end{aligned}$$

Solving out for U, $V(p_0)$, $V(1)$ and P yields

$$\begin{aligned} U &= \frac{1}{rD}\Big\{(r+c_1+c_2+c_3)(r+c_2+c_4)(r+\theta)\,b \\ &\qquad +\lambda(r+\theta)[(r+c_2+c_4)w(p_0)+c_1\mu_H]+(r+c_1+c_2+c_4)c_2\lambda\,a\Big\}, \end{aligned} \tag{21}$$

$$\begin{aligned} V(p_0) &= \frac{1}{rD}\Big\{(r+\lambda)(r+\theta)[(r+c_2+c_4)w(p_0)+c_1\mu_H]+(r+\lambda)c_2(r+c_1+c_2+c_4)\,a \\ &\qquad +[r(c_1c_4+(r+c_2+c_4)c_3)+(r(c_2+c_3)+(c_1+c_2+c_3)(c_2+c_4))\theta]\,b\Big\}, \end{aligned} \tag{22}$$

$$\begin{aligned} V(1) &= \frac{1}{rD}\Big\{[(r+\lambda)(r+\theta)c_1+r(r+c_2+c_3)(r+\theta)+r(r+c_2+\theta)\lambda]\,\mu_H \\ &\qquad +[(r+\theta)c_4+\theta c_2][(r+c_1+c_2+c_3)b+\lambda w(p_0)] \\ &\qquad\quad +[r(r+c_1+c_2+c_3)+(r+c_1+c_2+c_4)\lambda]c_2\,a\Big\}, \end{aligned} \tag{23}$$

$$\begin{aligned} P &= \frac{1}{rD}\Big\{[r(r+c_1+c_2+c_3)(r+c_2+c_4)+(r+c_1+c_2+c_4)(r+c_2)\lambda]\,a \\ &\qquad +(r+c_2+c_4)\theta[\lambda w(p_0)+(r+c_1+c_2+c_3)b]+c_1\lambda\theta\,\mu_H\Big\}, \end{aligned} \tag{24}$$

where $D \equiv (r+c_1+c_2+c_3)(r+c_2+c_4)(r+\theta)+(r+c_1+c_2+c_4)(r+c_2+\theta)\lambda$ and $w(p_0)$ is given by (2).

The lower bound a_L on the flow value of implementing a new firm satisfies $P = V(1)$. Setting (23) equal to (24) and solving out for a_L yields

$$a_L = \frac{(c_4-\theta)[(r+c_1+c_2+c_3)\,b+\lambda\,w(p_0)]+[(r+\theta)(r+c_1+c_2+c_3)+(r+\theta+c_1+c_2)\lambda]\mu_H}{(r+c_4)(r+c_1+c_2+c_3)+(r+c_1+c_2+c_4)\lambda}.$$

The upper bound on b satisfies $b_H = rV(p_0)$ or, using (22),

$$b_H = \frac{(r+\theta)[(r+c_2+c_4)w(p_0)+c_1\mu_H]+(r+c_1+c_2+c_4)c_2\,a}{(r+c_1+c_2+c_4)(r+c_2+\theta)}.$$

The lower bound on b satisfies $b_L = rV(0)-\lambda[V(p_0)-V(0)]$, where $rV(0)$ is the hypothetical flow value of accepting a demotion at the current employer without quitting. Similar to (3),

$$\begin{aligned} r\,V(0) &= \mu_L-(\delta+\theta)\,[V(0)-U]+\theta\gamma\,[P-V(0)] \\ &\qquad +\theta(1-\gamma)\alpha p_0\,[(1-\bar\varepsilon)V(1)+\bar\varepsilon V(p_0)-V(0)] \\ &= r\,\frac{\mu_L+c_2P+c_4U+c_5[(1-\bar\varepsilon)V(1)+\bar\varepsilon V(p_0)]}{r+c_2+c_4+c_5}, \end{aligned} \tag{25}$$

where c_2 and c_4 are defined as above and $c_5 \equiv \theta(1-\gamma)\alpha p_0$. At the lower bound $b = b_L$, we have $U = V(0)$ and (25) simplifies to $V(0) = U = \{\mu_L+c_2P+c_5[(1-\bar\varepsilon)V(1)+\bar\varepsilon V(p_0)]\}/\{(r+c_2+c_5)\}$. Setting this expression equal to (21) implicitly defines the lower bound $b_L = (r+\lambda)V(0)-\lambda V(p_0)$. The lower bound is strictly positive if and only if $V(0)/V(p_0) > \lambda/(r+\lambda)$.

By (15) and the above definitions, λ in equilibrium must satisfy

$$\lambda = c_2+\bar q\,c_3+(1-\bar q)c_4.$$

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