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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' characteristics at a 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 as in Jovanovic (1979). All these predictions are clearly supported in Brazilian data for the period 1995-2001. Calibration of our dynamic model indicates that employee spinoffs raise the share of workers in Brazil's private sector known to be of high match quality by 3.2 percent.

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An online appendix is available at:
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1 Introduction

Like cities, firms bring people together, in ways both planned and unplanned. A firm allows its employees to learn much 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 enterprise. At the same time, we take a conservative approach to the value that social capital generates, compared to the literature which connects teams to spinoff performance. In our model the value of social capital is realized by improving the match between workers and jobs: employee spinoffs are a vehicle for raising match quality. The value of social capital 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' capabilities and preferences 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. All of our results are estimated within firm by including spinoff or parent fixed effects.

Our model only allows social capital to influence aggregate output by changing the share of workers in new firms known to be of high match quality. Our estimates imply how this share evolves subsequently as firms age, in response to employer learning and worker turnover. Combining our results with the firm age distribution yields the estimate that employee spinoffs raise the average share of workers in Brazil's private sector known to be of high match quality by 3.2 percent.

There is a substantial literature on employee spinoffs, which has been primarily concerned with

[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.

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

A separate literature investigates the impact of social relationships on performance of workers within a given firm rather than on formation of new firms (e.g. Rotemberg 1994, Mas and Moretti 2009). Relationships between workers could have positive or negative effects on their performance, depending on the structure of incentives. Bandiera, Barankay, and Rasul (2008, 2009, 2010) in particular investigate the impact of pre-existing ties on worker performance, which is relevant to us insofar as the social ties that facilitated recruitment from the parent persist between the workers who join the spinoff. Specifically, if the spinoff structures incentives correctly, this could provide an alternative explanation for why turnover is lower for team members (they are more productive than non-team workers). This highlights the crucial role played by the dynamics of learning in our model. The alternative explanation does not predict that the team member survival premium declines monotonically with tenure, nor that the probability of departure from the parent to the spinoff eventually declines.

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 depart for spinoffs to that of workers who do not. We calibrate our model to estimate the aggregate impact of social capital in section 6. Section 7 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 *spinoff* entrepreneurs have an idea for a new firm, they learn about the match qualities of their colleagues with their planned firm through their interactions in the workplace. Their learning is different in nature from employer learning in that it results from direct observations of their colleagues' capabilities and preferences rather than inferences from signals generated by output.

Potential entrepreneurs learn match qualities of their close colleagues with their planned spinoff firm faster than the 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 the entrepreneurs' learning takes place at the moment when the idea arrives. An advantage of this formulation is that it allows for the possibility that, when the 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.[3] 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]We should also note that this alternative hypothesis would have difficulty explaining how employees with low ability remain in the labor force.

[3]Only 44.1 percent of spinoffs in our sample are in the same industry as their parents. This should not be surprising, since if the activity of the spinoff is similar to that of the parent it is more likely that it will be implemented inside the parent.

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 and a low-quality match generates output $\mu_L < \mu_H$ in continuous time, 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 an exogenous Poisson process of separation, as is already present in Moscarini (2005): 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 known 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

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

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

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

Workers are matched randomly to vacancies, so $p = p_0$ 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.[4] 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

[4] 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).

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. In this lemma and throughout the remainder of the paper we use the average hazard rate of retention (equals one minus the average hazard rate of separation) because it proves more convenient when reporting our empirical results.

Lemma 1. *For any cohort of employees with tenure τ at a firm i, the average wage and the average hazard rate of retention strictly increase 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 known in that cohort. The size of the cohort shrinks at rate $\dot{S}_i(\tau)/S_i(\tau) = -\{\delta + \phi(1-p_0)[1-q_i(\tau)]\}$ because a fraction $\phi(1-p_0)$ of cohort members with unknown match quality is discovered to have low match quality and quit. The measure of cohort workers with known match quality changes according to $\dot{S}_i^q(\tau) = -\delta S_i^q(\tau) + [S_i(\tau) - S_i^q(\tau)]\phi p_0$ because a fraction ϕp_0 of cohort members with unknown match quality is discovered to have high match quality and is internally promoted by the firm as workers of known match quality. This yields $\dot{S}_i^q(\tau)/S_i^q(\tau) = -\delta + [1/q_i(\tau)-1]\phi p_0$. By definition of $q_i(\tau)$, its 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

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

The fraction of cohort employees with known match quality increases with tenure at a rate that approaches zero as $q_i(\tau)$ approaches one.

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

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 form.

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 and elaborate details in the parts of our model that do 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 $[1-q_i(t)](1-\gamma)\alpha p_0$ 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.[5] 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.

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. *For any cohort of employees with tenure τ at a parent firm i from which spinoffs recruit at rate $\theta[1-q_i(t)](1-\gamma)\alpha p_0$, the average wage and the average hazard rate of retention strictly increase 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 known in that cohort. The size of the cohort shrinks at rate $\dot{S}_i(\tau)/S_i(\tau) = -\{\delta+\theta\gamma+[\theta(1-\gamma)\alpha p_0+\phi(1-p_0)][1-q_i(\tau)]\}$ because a fraction $(1-\gamma)\alpha p_0$ of cohort members with unknown match quality belongs to a spinoff entrepreneur's network and expects a strictly higher wage at her new firm, while a fraction $\phi(1-p_0)$ of cohort members

[5] 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.

with unknown match quality are discovered to have low match quality and quit. The measure of cohort workers with known match quality changes according to $\dot{S}_i^q(\tau) = -(\delta+\theta\gamma)S_i^q(\tau)+[S_i(\tau)-S_i^q(\tau)]\phi p_0$ because a fraction ϕp_0 of cohort members with unknown match quality is discovered to have high match quality and is internally promoted by the firm as workers of known match quality. This yields $\dot{S}_i^q(\tau)/S_i^q(\tau) = -(\delta+\theta\gamma)+[1/q_i(\tau)-1]\phi p_0$. By definition of $q_i(\tau)$, its 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

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

The result that the average cohort wage strictly increases with tenure now follows exactly as in Lemma 1. The average hazard rate of retention of the cohort is now $q_i(\tau)(1-\delta-\theta\gamma) + [1-q_i(\tau)][1-\delta-\theta\gamma-\phi(1-p_0)-\theta(1-\gamma)\alpha p_0] = 1-\delta-\theta\gamma - [1-q_i(\tau)][\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]$. Since $q_i(\tau)$ strictly increases with tenure, the cohort average hazard rate of retention strictly increases with tenure as well. $\square$

The share of cohort employees with known match quality at the parent firm increases faster under spinoff entrepreneurship than in the model without social capital and 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 an effective rate $\theta\alpha$. The former learning process adds to workers with known match quality and the latter learning process subtracts workers of unknown match quality from the cohort at the parent.

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 $1-[1-q_i(t)](1-\gamma)\alpha p_0$ 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.[6] At hiring, the match quality of outside employees or *non-team workers* is unknown and they receive a wage $w(p_0)$.

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 2.4. 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.

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

[6]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.

status outside formal work and call its value U. We can express the Bellman equations for an individual compactly as:

$$\begin{aligned} r\,V(p) &= w(p) - (\delta+\theta)\,[V(p)-U] \\ &\quad +\phi\big\{p\,[V(1)-V(p)] - (1-p)\,[V(p)-U]\,\big\} \\ &\quad +\theta\big\{\gamma\,[P-V(p)] + (1-\gamma)\alpha p_0\,[V(1)-V(p)]\,\big\} \end{aligned} \tag{3}$$

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

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

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

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

$$P = \frac{a + \theta U}{r + \theta}. \tag{9}$$

Equation (6) summarizes the vicissitudes to which an individual in our model is subject. When an employee 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 internally promoted, and with probability $\theta(1-\gamma)\alpha p_0$ he is recruited by members of his social network into their new firm. 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 A.

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 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 A.

2.5 Firm dynamics

We have seen that the ability of spinoff entrepreneurs (the partners) to mobilize social capital for their new firm depends inversely on the proportion of their colleagues whose match quality with the current employer is known. 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 $[1-q_i(t)]\,\phi p_0$. The flow of employees out of known status is $q_i(t)\,\delta + q_i(t)\,\theta\gamma$.[7] It follows that the change in the fraction of workers with known match quality is

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

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

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

As we expect, the steady state proportion of workers with known match quality at a firm increases with the rate of information arrival ϕ and decreases with the exogenous separation rate δ and the rate of spinoff entrepreneurship $\theta\gamma$. Importantly, the firm-level steady state share of known workers is independent of the social network size α. For an incumbent firm, the magnitude of α does not matter because any worker who departs for a spinoff must be of unknown match quality and will be replaced with another worker of unknown match quality; as a results network size is irrelevant for the evolution of q at incumbent firms. For an entrant, network size α at the parent matters for the initial share of known workers at birth, but the subsequent evolution is unaffected.

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 known match quality. Denote the parent's share of employees with known match quality by $q_p(t_{i0})$, where t_{i0} is the parent's age at the time when firm

[7] 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 $q_i(t)\delta$ was of known match quality at the firm so $q_i(t)$ decreases at a rate $q_i(t)\delta$ 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 $q_i(t)$ decreases at a rate $q_i(t)\theta\gamma$ from that flow. Note that the $[1-q_i(t)]\theta(1-\gamma)\alpha p_0$ 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 known match quality workers as they are replaced with new workers of unknown quality. Similarly, the $[1-q_i(t)]\phi(1-p_0)$ 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.

i spins off.[8] It follows that a spinoff i's initial share $q_i(0)$ of employees with known match quality is given by

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

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

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

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 $\phi(1-p_0)(1-\bar{q})\bar{M}$ endogenously quits as their match quality is revealed to be low, where $\bar{q}$ is the economy-wide fraction of employees with known match quality. For the economy to be in equilibrium, the flows into unemployment must be balanced by flows out of unemployment, yielding

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

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 establish that a stationary value of $\bar{q}$ exists, which implies a stationary value of λ by (15). In Appendix B, we establish the existence of a steady-state continuous probability density function of q for the population of firms, which implies that $\bar{q}$ exists since q is bounded between zero and one.

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

[8] 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: $\gamma = q_p(t_{i0})\gamma + [1-q_p(t_{i0})]\gamma$.

year.[9] 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.

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). 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). Muendler, Rauch, and Tocoian (2012, hereafter MRT) present further details on the data source and its application to employee spinoffs.

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. MRT use two alternative criteria and show the robustness of results under either criterion. For their preferred employee spinoff definition, they 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.[10] However, if this new firm absorbed at least seventy percent of the

[9] 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.

[10] Previous work for the parent is defined as a job spell of at least three months.

workers in one of the parent's plants and has a legal form such that it could be owned by the parent, MRT classify it as a divestiture (an employer-initiated spinoff) rather than an employee spinoff.[11] MRT find that the performance of spinoffs is superior to new firms without parents but inferior to divestitures. In particular, size at entry is larger for employee spinoffs than for new firms without parents but smaller than for divestitures, and subsequent exit rates (controlling for size at entry) for employee spinoffs are smaller than for new firms without parents but larger than for divestitures. MRT document that divestiture performance resembles that of new plants of existing firms entering new industries more than it resembles that of new firms. We will use MRT's criteria to distinguish employee spinoffs from new firms without parents and from divestitures. By these criteria, 29.0 percent of new firms in Brazil's domestically-owned private sector (that is, excluding firms with state or foreign ownership) in the period 1995-2001 with at least five employees are employee spinoffs.

4 Retention Hazards at Spinoffs

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. We prove the following proposition.

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

Proof. Let us define $q_{i0}(\tau)$ as the proportion of the non-team worker cohort that was hired at the founding time of firm i and that is of known match quality when the cohort has tenure τ. Note that $q_{i0}(0) = 0$. The average hazard rate of retention of the cohort is $q_{i0}(\tau)(1-\delta-\theta\gamma) + [1-q_{i0}(\tau)][1-\delta-\theta\gamma-\phi(1-p_0)-\theta(1-\gamma)\alpha p_0] = 1-\delta-\theta\gamma - [1-q_{i0}(\tau)][\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]$. Since team members are all of known match quality, their average retention hazard is given by $1-\delta-\theta\gamma$. The difference between the average retention hazards for team members and non-team workers is therefore the retention hazard gap

$$\beta \equiv [1-q_{i0}(\tau)][\phi(1-p_0)+\theta(1-\gamma)\alpha p_0] > 0.$$

Moreover, by Lemma 2 we have $\dot{q}_{i0}(\tau) > 0$, so the retention hazard gap β diminishes with cohort tenure. □

In an alternative world with perfect information it is hardly likely that an entrepreneur would find the best workers for her new firm among the relative handful available at her current employer. An entrepreneur might nevertheless choose these workers to conserve on upfront hiring costs, and gradually replace them with workers who are better fits as her firm matures, causing Proposition 1 to fail. 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

[11] A new firm that has a legal form such that it could be owned by the parent but that absorbed less than 70 percent of workers from a parent plant are classified as spinoffs. Empirical results are robust to dropping these firms.

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	.063	.102	.060	.046	.042	.025
	(.001)***	(.002)***	(.003)***	(.004)***	(.005)***	(.009)***
Obs.	147,504	101,104	57,036	30,706	13,860	5,204
R^2 (overall)	.044	.053	.028	.032	.054	.091
Mean Dep. variable	.770	.650	.733	.774	.805	.816
CNAE industry panels	540	526	511	480	429	343
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 MRT. Two observations per employee spinoff firm, one for team members and one for non-team workers. Control variables (not reported) are indicators for four-digit CNAE industry and firm birth cohort (1995-2000). Robust standard errors in parentheses: * significance at ten, ** five, *** one percent.

within the firm. That finding is consistent with a new firm's 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.[12] Note that all these employees joined the new firm in the same year. The key explanatory variable is an indicator for team members.[13] The coefficient on the team-member indicator is an estimate of the retention hazard gap β. 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 for one year, the proportion of team members that remains for a second year is 10.2 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: founding team members whose match quality is known from the time at the previous employer are retained more frequently than non-team members, but as the spinoff partners learn about the match quality of non-

[12]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.

[13]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.

team members the difference in the retention rate declines. A single exception to the monotonic decline in the retention hazard gap occurs for the increase in the retention hazard gap from the first to the second year of employment (between column 1 and 2). This initial increase in the hazard gap 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.

Evidence from a further investigation of the first-year deviation is consistent with the interpretation that the fall in the mean retention hazard rate in Table 1 from 0.77 in $t+1$ to 0.65 in $t+2$ is primarily a consequence of the newness of the spinoff firm. We computed mean retention hazards in $t+1$ and $t+2$ for the sample of new firms in RAIS without parents, on the one hand, and also for the sample of newly hired workers at existing firms, on the other hand. We obtained 0.62 and 0.53 for the former sample of hires at new firms, and 0.62 and 0.61 for the latter sample of new hires at incumbent firms. A plausible explanation of the former result is that employer learning about worker match quality is hampered when a firm is just starting up, leading to high retention rates in its first year of operation. Even for existing firms in the latter sample, however, the retention hazard rate for new workers decreases slightly from the first to the second year of their employment. This is consistent with the well-known tendency for separation hazard rates to rise at the very beginning of employment before falling (see e.g. Farber 1999), which can be explained by the original employer learning model of Jovanovic (1979) but is missed in our simplification.[14]

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.[15] Third, even if a firm survives it may lose all its team members, all its other startup workers, or both.

Empirically, workers differ in many characteristics that may influence their retention rates. We therefore turn to evidence at the individual worker level. We start with the same set of worker control variables that were included in log wage regressions by Menezes-Filho, Muendler, and Ramey (2008) in their work with the RAIS data. They used education categories, a quartic in potential experience (age less typical age at completion of 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 a worker's previous employer, because sorting of workers into their current occupations is arguably endogenous to their match qualities at the spinoff firms.[16] 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.

[14]Farber (1999, pp. 2463-2464) provides a good intuitive description of the Jovanovic (1979) 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, separation rates increase."

[15]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.

[16]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	20.109	18.568	16.631
	(.0115)	(.0139)	(.012)
Middle School or less	.623	.653	.654
	(.0005)	(.0006)	(.0005)
Some High School	.274	.259	.270
	(.0005)	(.0006)	(.0005)
Some College	.030	.027	.026
	(.0002)	(.0002)	(.0002)
College Degree	.072	.060	.050
	(.0003)	(.0003)	(.0002)
Same *CNAE*	.588	.193	
	(.0005)	(.0006)	
Prev. Prof. or Manag'l. Occ.	.133	.100	
	(.0003)	(.0004)	
Prev. Tech'l. or Superv. Occ.	.175	.177	
	(.0004)	(.0005)	
Prev. Unskilled Wh. Collar Occ.	.161	.168	
	(.0004)	(.0005)	
Prev. Skilled Bl. Collar Occ.	.401	.404	
	(.0005)	(.0006)	
Prev. Unskilled Bl. Collar Occ.	.130	.150	
	(.0003)	(.0005)	
Prev. Log monthly wage	5.697	5.408	
	(.0009)	(.001)	
Prev. Log months of tenure	3.118	2.581	
	(.0012)	(.0013)	
Female employee	.293	.269	.302
	(.0005)	(.0006)	(.0005)
Obs.	974,708	598,565	842,032

Source: RAIS 1995-2001, workers at employee spinoff firms.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in MRT. Potential labor force experience equals age minus years of education. Previous occupations and wages are those at last employer. Same *CNAE* only defined for workers that had non-missing *CNAE* data at both the spinoff and the last employer. Missing data for education: Team 3,368, trackable non-team 2,386, all non-team 3,661. Missing data for potential experience: Team 4,224, trackable non-team 3,015, all non-team 4,952. Missing data for same *CNAE*: Team 42,372, trackable non-team 88,970. Missing data for previous occupation: Team 19,820, trackable non-team 21,746. Missing data for previous wage: Team 8,463, trackable non-team 7,055. Standard errors in parentheses.

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. In the same spirit, we also add an indicator for whether the worker was previously employed in the same 4-digit CNAE industry as the spinoff, and the log of months of tenure at the previous employer, measuring the time the worker had to absorb specialized skills.

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 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, their previous employers are more likely to have been in the same industry, and they received higher wages and had longer tenure at their previous employers. It is 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 reduction in that gap with tenure predicted by Proposition 1.[17]

Tables 3 and 4 repeat the retention hazard regressions of Table 1 at the individual level. Table 3 considers the full worker sample and Table 4 restricts the sample of non-team workers to those who are trackable. 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. In Table 3, levels of education above the reference category of some middle school or less are associated with greater retention hazards. However, inclusion of education levels and other inherent worker characteristics (not linked to previous jobs) leaves the impact of team membership on retention hazards virtually unchanged from Table 1. In Table 4, log of months tenure at previous job has a strong positive association with retention hazards in all periods, as does log of previous monthly wage in periods $t+2$ to $t+4$. Relative to Table 1, the coefficients on team member are reduced by about 20 percent in periods $t+2$ to $t+4$ and about 30 percent in period $t+5$, and an increase in the coefficient for period $t+6$ disrupts the otherwise monotonic decline in the retention hazard gap with tenure. Nevertheless, support for Proposition 1 remains strong.[18]

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

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

[18] Results are qualitatively unchanged if we replace the six occupational categories with a full set of 354 occupation indicators.

Table 3: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF

	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	.106	.060	.043	.036	.021
	(.002)***	(.002)***	(.002)***	(.002)***	(.004)***	(.005)***
Some High School	.024	.032	.025	.010	.011	.0006
	(.003)***	(.005)***	(.004)***	(.005)**	(.006)*	(.010)
Some College	.018	.017	.013	.003	-.003	.091
	(.004)***	(.007)**	(.007)**	(.008)	(.014)	(.039)**
College Degree	.018	.020	.012	-.009	-.003	.028
	(.004)***	(.005)***	(.007)*	(.008)	(.010)	(.027)
Pot. lab. force exp.	-.005	-.0001	.007	.007	.005	.005
	(.0008)***	(.001)	(.002)***	(.002)***	(.003)*	(.004)
Sq. Pot. lab. force exp.	.0003	.0002	-.0002	-.0002	-.0002	-.00007
	(.00005)***	(.00009)**	(.0001)**	(.0001)*	(.0002)	(.0003)
Cub. Pot. lab. force exp.	-6.50e-06	-6.64e-06	3.76e-06	2.62e-06	4.15e-06	-1.42e-06
	(1.22e-06)***	(2.06e-06)***	(2.63e-06)	(3.33e-06)	(5.04e-06)	(8.09e-06)
Qrt. Pot. lab. force exp.	4.57e-08	5.57e-08	-2.90e-08	-1.38e-08	-3.86e-08	1.73e-08
	(1.02e-08)***	(1.65e-08)***	(2.17e-08)	(2.86e-08)	(4.25e-08)	(6.90e-08)
Female employee	-.010	-.002	.005	-.011	-.009	.021
	(.006)*	(.009)	(.010)	(.014)	(.022)	(.033)
Obs.	1,427,971	774,618	352,405	159,610	67,602	25,741
R^2	.257	.236	.238	.254	.257	.302
Mean Dep. variable	.756	.668	.754	.791	.816	.795
Firm panels	73,361	50,225	28,283	15,186	6,816	2,555

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 MRT. Coefficients for interactions of female with all other worker characteristics are not shown. 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.

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 thereafter (tables 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 but its effect is negligible.

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

Table 4: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, TRACKABLE WORKERS

	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	.061	.085	.046	.038	.029	.033
	(.003)***	(.003)***	(.003)***	(.004)***	(.005)***	(.009)***
Some High School	.025	.015	.015	.002	.0001	-.027
	(.004)***	(.005)***	(.005)***	(.005)	(.007)	(.018)
Some College	.029	-.012	-.004	-.013	-.014	.069
	(.007)***	(.007)*	(.008)	(.010)	(.017)	(.032)**
College Degree	.038	-.029	-.007	-.032	-.024	-.027
	(.008)***	(.006)***	(.009)	(.010)***	(.013)*	(.020)
Pot. lab. force exp.	-.001	-.0009	.006	.007	.003	.002
	(.001)	(.002)	(.002)***	(.003)***	(.004)	(.006)
Sq. Pot. lab. force exp.	.0001	.0001	-.0003	-.0003	-.0002	.00007
	(.00007)*	(.0001)	(.0001)**	(.0002)	(.0002)	(.0004)
Cub. Pot. lab. force exp.	-2.81e-06	-4.46e-06	5.85e-06	3.76e-06	4.00e-06	-4.68e-06
	(1.53e-06)*	(2.61e-06)*	(3.30e-06)*	(4.15e-06)	(6.13e-06)	(1.00e-05)
Qrt. Pot. lab. force exp.	1.92e-08	3.75e-08	-4.96e-08	-2.07e-08	-3.96e-08	4.43e-08
	(1.24e-08)	(2.11e-08)*	(2.73e-08)*	(3.53e-08)	(5.15e-08)	(8.97e-08)
Same *CNAE*	.005	.021	.013	-.0006	-.0007	-.031
	(.004)	(.004)***	(.004)***	(.007)	(.008)	(.013)**
Prev. Prof./Manag'l. Occ.	.037	-.011	-.025	-.006	-.015	.022
	(.007)***	(.008)	(.006)***	(.008)	(.009)*	(.027)
Prev. Tech'l./Superv. Occ.	.023	-.005	-.012	-.004	-.004	.008
	(.005)***	(.006)	(.005)**	(.007)	(.010)	(.028)
Prev. Unsk. Wh. Coll. Occ.	.008	-.006	-.011	-.0007	-.0007	.008
	(.004)**	(.006)	(.006)**	(.007)	(.010)	(.026)
Prev. Skld. Bl. Collar Occ.	.019	-.005	-.013	-.006	-.004	-.024
	(.006)***	(.006)	(.005)**	(.006)	(.008)	(.017)
Prev. Log monthly wage	-.050	.041	.018	.014	.009	.020
	(.008)***	(.004)***	(.004)***	(.004)***	(.006)	(.014)
Prev. Log months of tenure	.037	.037	.026	.017	.015	.020
	(.002)***	(.003)***	(.002)***	(.002)***	(.003)***	(.004)***
Obs.	1,072,193	580,901	262,602	115,082	46,030	16,293
R^2	.279	.256	.249	.273	.276	.294
Mean Dep. variable	.774	.684	.764	.796	.821	.806
Firm panels	68,270	45,053	23,861	12,363	5,391	1,929

Source: RAIS 1995-2001, employee spinoff firms with at least one non-team member at time of entry; sample of workers who can be tracked to previous formal sector employment.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in MRT. Results for male workers; female indicator and coefficients for interactions of female with all other worker characteristics not shown. 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. Same *CNAE* only defined for workers that had non-missing *CNAE* data at both the spinoff and the last job spell. 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.

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 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.[19] 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.

The two panels of Table 5 report the regressions from Tables 3 and 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 the coefficient on this interaction is positive and significant for the first four years of employment, offering some support for the hypothesis that more productive spinoff firms are able to recruit workers with innately higher ability from their parents. 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.[20]

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. We now turn to complementary evidence from separation hazards and worker tenure at parent firms.

5 Departure Hazards 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, the rate at which workers depart from the parent to a spinoff (where they become founding team members) is, as a function of tenure,

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

[19] 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.

[20] 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.

Table 5: RETENTION HAZARD GAP, PARENTS SURVIVING TO 2001

	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	.089	.106	.059	.049	.026	.018
	(.005)***	(.004)***	(.004)***	(.005)***	(.006)***	(.009)**
Team mmb. $\times$ Dff. Log empl.	.015	.006	.002	.003	-.003	.002
	(.001)***	(.001)***	(.001)**	(.002)**	(.002)*	(.003)
Mean Log size ratio	-1.53	-1.514	-1.497	-1.676	-1.945	-1.667
Adjusted Team member coeff.	0.066	0.096	0.055	0.043	0.032	0.014
Obs.	824,986	419,007	199,206	85,630	34,618	13,042
R^2	.253	.236	.232	.254	.257	.213
Mean Dep. variable	.759	.673	.761	.800	.830	.834
Firm panels	38,601	25,768	14,441	7,724	3,523	1,281

	Trackable 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	.077	.083	.044	.045	.023	.025
	(.006)***	(.005)***	(.005)***	(.006)***	(.009)**	(.018)
Team mmb. $\times$ Dff. Log empl.	.016	.007	.003	.003	-.002	.001
	(.002)***	(.001)***	(.001)*	(.002)*	(.003)	(.005)
Mean Log size ratio	-1.478	-1.423	-1.379	-1.545	-1.842	-1.554
Adjusted Team member coeff.	0.053	0.073	0.040	0.040	0.028	0.023
Obs.	634,940	318,744	152,438	63,218	23,603	8,377
R^2	.272	.252	.240	.267	.283	.243
Mean Dep. variable	.776	.689	.772	.806	.833	.837
Firm panels	36,184	23,303	12,357	6,381	2,814	985

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; all workers (upper panel) and sample of workers who can be tracked to previous formal sector employment (lower panel).
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in MRT. All regressions include same controls as in Table 3. Difference in log employment is for spinoff in birth year and parent in previous year. Adjusted team member coefficient is defined as the team member coefficient added to the product of the mean log size ratio and the coefficient on the interaction term. Clustered standard errors at the level of teams in parentheses: * significance at ten, ** five, *** one percent.

where $q_i(\tau)$ denotes the fraction of workers whose match quality is known in a given worker cohort $S_i(\tau)$ with tenure τ at parent firm i.[21] 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* $\dot{U}_i(\tau)/S_i(\tau) \equiv \delta + \phi(1-p_0)[1-q_i(\tau)]$, 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 at 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 2. *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* $\dot{\alpha}_i(0)/\alpha_i(0) > \dot{q}_i(0)/[1-q_i(0)]$ *and* $\dot{\alpha}_i(\hat{\tau})/\alpha_i(\hat{\tau}) < \dot{q}_i(\hat{\tau})/[1-q_i(\hat{\tau})]$ *for some finite tenure* $\hat{\tau}$.

Proof. The departure hazard of workers who join a founding spinoff team is

$$\dot{T}_i(\tau)/S_i(\tau) \equiv \theta(1-\gamma)\alpha_i(\tau)p_0[1-q_i(\tau)].$$

By this definition, $\partial[\dot{T}_i(\tau)/S_i(\tau)]/\partial\tau > 0$ if and only if $\dot{\alpha}_i(\tau)/\alpha_i(\tau) > \dot{q}_i(\tau)/[1-q_i(\tau)]$, 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 low departure hazard for parent employees with long tenure is 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 arise if it takes time for parent employees to become members of a social network.

Proposition 3. *The separation hazard of workers who become unemployed strictly declines in tenure at any level of parent-firm tenure.*

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

[21] In addition, parent workers become partners at a 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.

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 separations.

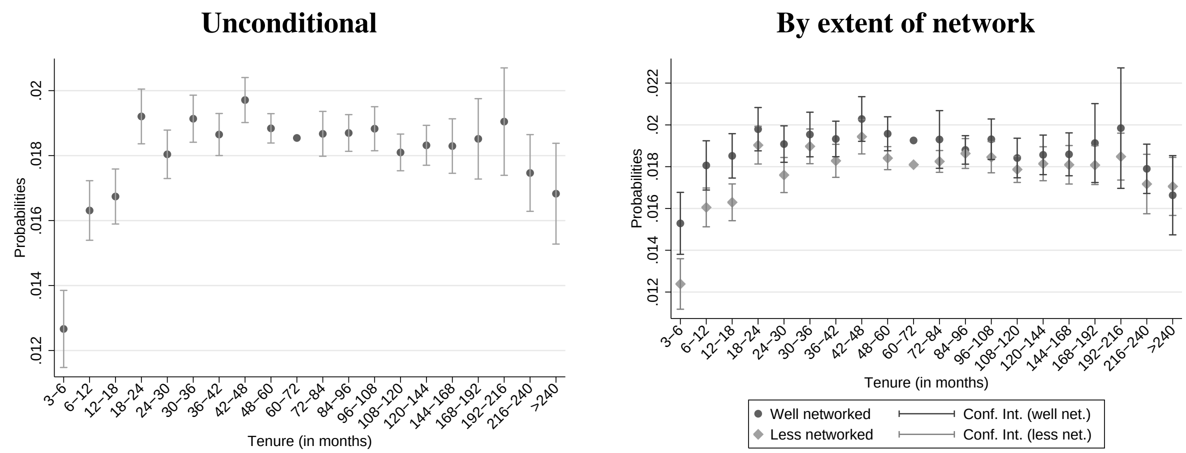
When comparing tenure at a parent firm between workers who join a spinoff and workers who remain at the parent, we must be careful to identify the correct choice set facing the entrepreneurs who are recruiting the workers. This consideration leads us to define the dependent variable for separation to 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. For this minority of cases it appears 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.[22]

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 wish to separate from a dying parent regardless of match quality.[23]

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: our first bin contains workers with a tenure of 3-6 months at the parent, the tenth (and midpoint) bin is for 60-72 months of tenure, and the twentieth bin groups workers with more than 240 months (20 years) of 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), and condition on parent-year fixed effects. We include in the sample workers who continue at the parent, parent workers who depart to join a spinoff and parent workers who separate for other RAIS employment or unemployment, but we omit from the sample parent workers who are reported to retire or die. We cluster the standard errors at the parent-year level. Table C.1 in Appendix C shows the full set

[22]The assumption of our model that workers exit firm social networks when they separate from the firms is a simplification. Unemployed members of the social network of a spinoff entrepreneur will accept a job offer if the parties know that the unemployed network member is of high match quality with the planned firm, but not if they know the unemployed member is of low match quality.

[23]All workers with less than three months of tenure at the parent are dropped from the sample. Recall from Section 3 that when MRT 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 is defined as a job spell of at least three months (footnote 10).



Source: RAIS 1995-2001, parent firms 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 MRT. 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 a departure indicator 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. Depicted probabilities are tenure-bin coefficients plus the predicted value from remaining regressors (including constant for omitted tenure bin coefficient of 60 to 72 months). Table C.1 in Appendix C shows the full set of coefficient estimates for all graphs. 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**

of coefficient estimates.

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 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 2.

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 354 recorded occupations).[24] 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 relatively high α_i (with many occupation changes) should more frequently depart from parents to spinoffs than less networked workers, whereas the alternative hypothesis of fast employer learning predicts the opposite.

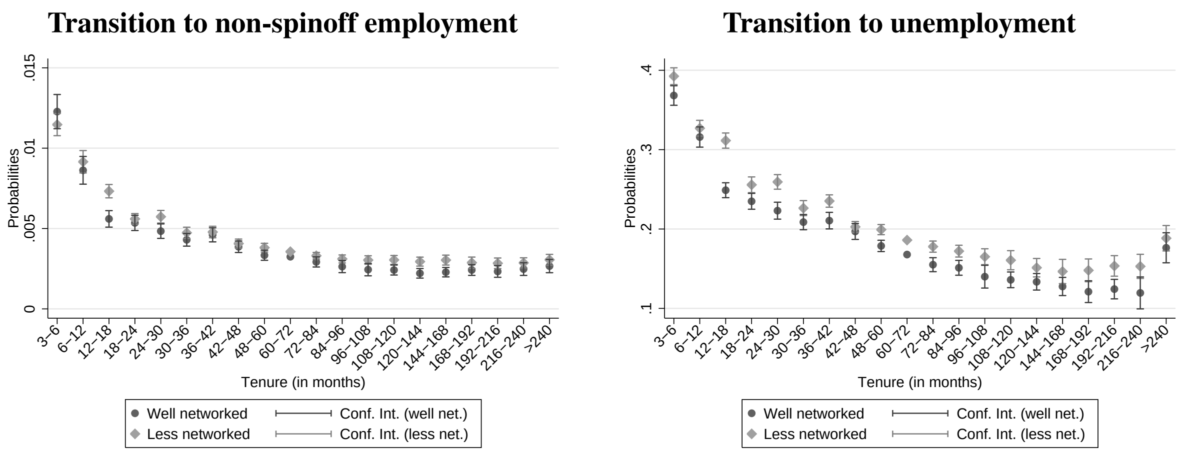
The right-hand graph in Figure 1 depicts the tenure bin results for both well networked employees with at least one occupation change (*well networked employees*) and employees with no occupation change at their current employer (*less networked employees*). In line with our social-capital explanation, 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.

We now turn to Proposition 3. 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.[25] This separation hazard strictly declines with parent-firm tenure, just as Proposition 3 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 now (not higher as before) 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 shift

[24]In our version of RAIS, occupations are reported at the CBO (*Classificação Brasileira de Ocupações*) 3-digit level which classifies occupations into 354 categories.

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



Source: RAIS 1995-2001, parent firms 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 MRT. 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 a departure indicator 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). Table C.1 in Appendix C shows the full set of coefficient estimates for the left graph. Confidence intervals (95% significance) from clustered standard errors at the parent-year level by tenure-bin indicator, relative to omitted tenure bin.

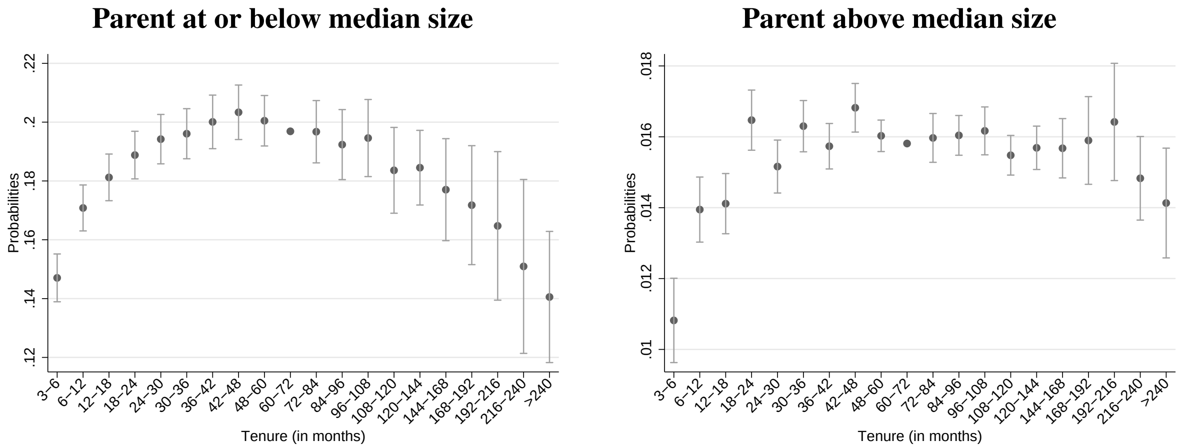
Figure 2: **Separation Hazards of Parent Workers to Non-spinoff Employment and Unemployment**

to unemployment, self employment or informal work (outside RAIS).[26] This separation hazard strictly declines with parent-firm tenure, just as Proposition 3 predicts, and similarly for both well networked and less networked employees.

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. 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 employees, giving the spinoff a chance to recruit them. Accordingly, we split the sample into parent firms with size at or below median employment (62 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

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



Source: RAIS 1995-2001, parent firms 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 MRT. 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 a departure indicator 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 62 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). Table C.1 in Appendix C shows the full set of coefficient estimates for the left graph. 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 by Parent Size**

(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. The qualitative contrast between the single-peaked left- and plateau-like right-hand graphs is robust to splitting the parent sample at the 25th or 75th percentile of parent employment.

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 with their planned firms initially faster than employers learn the same workers' match qualities with their firms.

6 Quantifying the Aggregate Impact of Social Capital

In our model aggregate output is

$$\bar{X} = \bar{M}\bar{x} = \bar{M}\left\{\bar{q}\,\mu_H + (1-\bar{q})[p_0\,\mu_H + (1-p_0)\mu_L]\right\}, \tag{16}$$

where we used equation (1) to substitute for mean output per firm $\bar{x}$.[27] Aggregate output $\bar{X}$ increases with the economy-wide fraction of workers with known match quality $\bar{q}$. The only means by which social capital influences aggregate output in our model is a rise in the share of workers known to be of high match quality at firm entry, which in turn changes the economy-wide fraction of employees with known match quality $\bar{q}$. We denote by $\bar{q}_{\alpha=0}$ the economy-wide fraction of workers with known match quality in the absence of social capital ($\alpha = 0$). That benchmark social capital level allows us to measure the aggregate impact of social capital by $(\bar{q} - \bar{q}_{\alpha=0})/\bar{q}_{\alpha=0}$.

To calibrate $\bar{q}$ and infer the counterfactual $\bar{q}_{\alpha=0}$, our first step is to use the fact that in our model $q_i(t)$, the share of workers of known match quality in firm i of age t, is determined entirely by its initial value $q_i(0)$ and the age of the firm. In the absence of social capital, $q_i(0) = 0$ for all i, and we use this to compute $q(t)_{\alpha=0}$, the share of workers of known match quality for every firm of age t in the absence of social capital. In the presence of social capital, we incorporate the aforementioned fact that 29.0 percent of new Brazilian firms in our data are employee spinoffs, as opposed to 100 percent as assumed in our general equilibrium model.[28] For all these employee spinoffs we assume that $q_i(0)$ equals $q(0)_{spin}$, the mean of team member share of founding workers for employee spinoffs in our data.[29] We use this to compute $q(t)_{spin}$, the share of workers of known match quality for every employee spinoff firm of age t. We assign $q_i(0) = 0$ to the other 71 percent of new Brazilian firms in our data. Our estimate of aggregate q for each firm age is then given by $q(t)_{agg} = 0.29q(t)_{spin} + 0.71q(t)_{\alpha=0}$. Thus our estimate is best thought of as the aggregate impact of social capital embodied in employee spinoffs only, rather than in all firms.

We can compute $q(t)_{\alpha=0}$ and $q(t)_{spin}$ using equation (12) and the respective initial conditions $q_i(0)_{\alpha=0} = 0$ and $q_i(0) = q(0)_{spin}$ for all i, to obtain

$$q(t)_{\alpha=0} = q^*(1 - \exp\{-(\delta + \theta\gamma + \phi p_0)t\}) \tag{17}$$

and

$$q(t)_{spin} = q^* + [q(0)_{spin} - q^*] \exp\{-(\delta + \theta\gamma + \phi p_0)t\}, \tag{18}$$

where q^* is given by equation (11). By equation (17), new firms that do not start out as employee spinoffs have a zero share of employees with known match quality at birth and subsequently raise this share toward the long-term steady state level q^*. Employee spinoffs, in contrast, may start out with a share of employees with known match quality above or below the steady state share. The reason is that the initial share depends on the parents' share of employees with known match quality at time of spinoff, which determines how many founding team members the spinoff can attract.

[27] 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.

[28] In an Online Appendix, we estimate $(\bar{q} - \bar{q}_{\alpha=0})/\bar{q}_{\alpha=0}$ adhering to our general equilibrium model as closely as possible. In particular, we maintain the assumptions that all firms are the same size and all new firms are employee spinoffs. Our estimate is 0.044, larger than the estimate of 0.032 we obtain below, but not so much larger given that the potential impact of social capital more than triples in moving from 29 to 100 percent of new firms as employee spinoffs. The reason for the small difference is that with parent firms the same size as their spinoffs, instead of much larger, the calibrated share of team members in founding workers is much smaller than the empirical share.

[29] Depending on the parent's share of workers with known match quality at time of spinoff, some spinoffs start with lower and others with higher shares of workers with known match quality at entry. For calibration we use the average.

The rate at which workers separate from firms to become entrepreneurs, $\theta\gamma$, is the product of two small numbers so can have little quantitative impact. Moreover, we do not observe firm owners in our data. We therefore assume $\gamma = 0$, and equations (17) and (18) simplify to

$$q(t)_{\alpha=0} = \frac{\phi p_0}{\delta + \phi p_0}\left(1 - \exp\{-(\delta + \phi p_0)t\}\right) \tag{19}$$

and

$$q(t)_{spin} = \frac{\phi p_0}{\delta + \phi p_0} + \left[q(0)_{spin} - \frac{\phi p_0}{\delta + \phi p_0}\right]\exp\{-(\delta + \phi p_0)t\}, \tag{20}$$

where we have substituted for q^* using equation (11). To use equations (19) and (20) we need to estimate δ, the rate at which workers exogenously separate from firms regardless of match quality, and the internal promotion rate ϕp_0 at which workers of unknown match quality are discovered to be of high match quality.

Appendix D shows how δ and ϕp_0 can be estimated using the levels and changes over time in the coefficients on the team member indicators from our retention hazard regressions in Section 4. This is possible because team members only separate from firms exogenously, at rate $\delta + \theta\gamma$, whereas non-team workers also separate endogenously, due to both employer learning and learning by spinoff entrepreneurs. Our assumption that $\gamma = 0$ thus makes estimation of δ from team member retention hazard rates straightforward. To eliminate the impact of recruitment by spinoff entrepreneurs, we drop spinoff firms from the sample if they have spinoffs of their own and then re-estimate Table 3, the retention hazard regressions with the broadest coverage of firms and workers. The results, reported in Table D.1 in the appendix, differ little from those in Table 3. The difference between the retention hazards of team members and non-team workers is then due to employer learning only. Finally, because of the apparent delay in employer learning we observe for new firms, we assume that the share of non-team workers of known match quality is zero at the beginning of the second instead of the first year of operation of the employee spinoff.

We obtain the estimates $\delta = 0.20$ and $\phi p_0 = 0.24$. Table D.2 reports the intermediate calculations. The estimates yield $q^* = 0.55$. Workers of known match quality are separating and workers of unknown match quality are becoming known (to be of high match quality) at roughly equal rates, leading to a steady state share of workers of known match quality close to one-half. For employee spinoff firms, the initial share of workers of known match quality, $q(0)_{spin}$, equals 0.489 in our data, not far below q^*.

We then compute $\bar{q}_{\alpha=0}$ and $\bar{q}$ by taking weighted averages of $q(t)_{\alpha=0}$ and $q(t)_{agg}$, respectively, using employment by firm age in Brazil's domestically-owned private sector for the period 1995-2001. This implicitly treats the distribution of employment by firm age in this period as the steady-state distribution. In our general equilibrium model, in which all firms have the same constant size, weighting with employment by firm age is equivalent to weighting with the number of firms of each age. Since in reality older firms tend to be larger, we use employment weighting rather than firm-number weighting to avoid upward bias in our estimate of the aggregate impact of social capital which could arise from under-weighting older firms for which the impact of social capital has worn off. We do not, however, adjust our formulas for $q(t)_{\alpha=0}$ and $q(t)_{spin}$ to account for any firm growth. As shown in Table D.3, 93 percent of the aggregate impact of social capital occurs in firms ages zero to four, over which average firm size increases by less than two employees. We also do not adjust these formulas for any delay in employer learning by new firms. Such an adjustment would increase the estimated impact of social capital because it would magnify the importance of a firm's initial share of workers of known match quality.

The estimates we obtain of the average share of workers known to be of high match quality in Brazil's domestically owned private sector during the period 1995-2001 are $\bar{q}_{\alpha=0} = 0.487$ without social capital, and $\bar{q} = 0.502$ with social capital. Both estimates are close to our estimate of the steady state share of firm workers known to be of high match quality because Brazil's employment is dominated by old firms. Plugging our estimates into the formula $(\bar{q} - \bar{q}_{\alpha=0})/\bar{q}_{\alpha=0}$, we see that social capital increases the average share of workers known to be of high match quality by 3.2 percent.

7 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. The impact of this social capital shows up in the dynamics of employee retention at spinoff firms, the dynamics of employee departures for spinoffs from parent firms, and ultimately in aggregate output through the economy-wide share of employees known to be of high match quality with their employers at startup.

The capabilities and preferences of colleagues by no means exhaust the list of what employees learn inside a parent firm. Studies of high-tech industries 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, employees give us the opportunity to observe what they must have learned. As data for spinoffs and their parents become increasingly available, we can expect the study of employee spinoffs to reveal much more about the nature and value of learning inside firms.

Appendix

A 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 $c_1 \equiv [\phi + \theta(1-\gamma)\alpha]p_0$, $c_2 \equiv \theta\gamma$, $c_3 \equiv \delta + \theta + \phi(1-p_0)$ 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

$$\begin{aligned}
U &= \frac{1}{rD}\Big\{(r+c_1+c_2+c_3)(r+c_2+c_4)(r+\theta)\, b \qquad \text{(A.1)} \\
&\quad +\lambda(r+\theta)[(r+c_2+c_4)w(p_0) + c_1\mu_H] + (r+c_1+c_2+c_4)c_2\lambda\, a\Big\}, \\
V(p_0) &= \frac{1}{rD}\Big\{(r+\lambda)(r+\theta)[(r+c_2+c_4)w(p_0) + c_1\mu_H] + (r+\lambda)c_2(r+c_1+c_2+c_4)\, a \qquad \text{(A.2)} \\
&\quad +[r(c_1c_4 + (r+c_2+c_4)c_3) + (r(c_2+c_3) + (c_1+c_2+c_3)(c_2+c_4))\theta]\, b\Big\}, \\
V(1) &= \frac{1}{rD}\Big\{[(r+\lambda)(r+\theta)c_1 + r(r+c_2+c_3)(r+\theta) + r(r+c_2+\theta)\lambda]\,\mu_H \qquad \text{(A.3)} \\
&\quad +[(r+\theta)c_4 + \theta c_2][(r+c_1+c_2+c_3)b + \lambda w(p_0)] \\
&\quad\quad +[r(r+c_1+c_2+c_3) + (r+c_1+c_2+c_4)\lambda]c_2\, a\Big\}, \\
P &= \frac{1}{rD}\Big\{[r(r+c_1+c_2+c_3)(r+c_2+c_4) + (r+c_1+c_2+c_4)(r+c_2)\lambda]\, a \qquad \text{(A.4)} \\
&\quad +(r+c_2+c_4)\theta[\lambda w(p_0) + (r+c_1+c_2+c_3)b] + c_1\lambda\theta\,\mu_H\Big\},
\end{aligned}$$

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 (A.3) equal to (A.4) 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 (A.2),

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

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),

$$\begin{aligned} r\,V(0) &= \mu_L - (\delta+\theta)\,[V(0) - U] + \theta\gamma\,[P - V(0)] \\ &\qquad +\theta(1-\gamma)\alpha p_0\,[V(1) - V(0)] \\ &= r\,\frac{\mu_L + c_2 P + c_4 U + c_5 V(1)}{r + c_2 + c_4 + c_5}, \end{aligned} \tag{A.5}$$

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 (A.5) simplifies to $V(0) = U = \{\mu_L + c_2 P + c_5 V(1)\}/\{(r + c_2 + c_5)\}$. Setting this expression equal to (A.1) 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

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

B Steady-state Distribution of Known Match-quality Share q

As derived in Subsection 2.5 of the text, a firm i has a share $q_i(t) \in [0, 1]$ of known workers at age t and $q_i(t)$ evolves deterministically with

$$q_i(t) = [q_i(0) - q^*]\exp\{-\eta t\} + q^*, \tag{B.1}$$

restating (14) from the text, where

$$q_i(0) = [1 - q_p(t_{i0})]\psi \tag{B.2}$$

by (13) in the text, $q_p(t_{i0})$ is the parent's share of known workers at spinoff birth,

$$\psi \equiv (1-\gamma)\alpha p_0 < 1, \;\; \eta \equiv \delta + \theta\gamma + \phi p_0,$$

and

$$q^* = \frac{\phi p_0}{\delta + \theta\gamma + \phi p_0} = \frac{\phi p_0}{\eta} \tag{B.3}$$

by (11) in the text.

Age evolves deterministically, conditional on survival. Given a Poisson process of exit with rate θ, the fraction of firms with age $t_i \leq t$ is given by the exponential cumulative distribution function

$$G(t) = 1 - \exp\{-\theta t\}. \tag{B.4}$$

The reason is that the probability for the waiting time W until the (first) Poisson event arrives to exceed t is equal to $\Pr(W > t) = G(t)$ under a Poisson process. Note that age and $q(0)$ are independent. The probability density function of firm age is $g(t) = G'(t) = \theta[1 - G(t)] = \theta\exp\{-\theta t\}$.

We want to establish the existence of a continuous probability density function $f(q)$ that measures the fraction of firms with a share q of workers with known match quality. We begin by defining $\rho(q,t)$ as the mass of firms with known share q and age t years. Accordingly, the mass of firms with known share q at birth (age zero) is $\rho(q,0)$. As t years pass, their initial known share is related forward to the present known share for those firms that survive by (B.1): $q(0) = [q(t) - q^*]\exp\{\eta t\} + q^*$. Since survival is independent of q, we can infer that

$$\rho(q,t) = [1 - G(t)] \cdot \rho(q,0) = [1 - G(t)] \cdot \rho\Big((q - q^*)\exp\{\eta t\} + q^*, 0\Big). \tag{B.5}$$

By the spinoff process under (B.2), the mass of newborn firms with $q(0)$ depends on the mass of parents with $q_p(t_{i0})$. Integrating over the age distribution of parents, and multiplying by the hazard rate at which a spinoff happens to the parents, we obtain:

$$\begin{aligned}
\rho(q,0) &= \theta \int_0^\infty \rho(q_p,t)\, g(t)\, \mathrm{d}t \\
&= \theta \int_0^\infty [1 - G(t)]\, \rho\Big((q_p - q^*)\exp\{\eta t\} + q^*, 0\Big) g(t)\, \mathrm{d}t \\
&= \theta^2 \int_0^\infty \rho\Big([(1 - q/\psi) - q^*]\exp\{\eta t\} + q^*, 0\Big)[1 - G(t)]^2\, \mathrm{d}t,
\end{aligned} \tag{B.6}$$

where $g(t) = G'(t) = \theta[1 - G(t)]$ is the density function of (parent) age. The substitution on the second line follows using (B.5) and on the third line using (B.2).

Equation (B.6) defines a mapping T from the space $C[0,1] = \{f : [0,1] \to [0,1], f \text{ continuous}\}$ of continuous functions on $[0,1]$ to itself. Applied to our context, and defining $h(x) \equiv \rho(x,0)$, the mapping can be written as

$$Th(q) = \theta^2 \int_0^\infty h([(1 - q/\psi) - q^*]\exp\{\eta t\} + q^*)[1 - G(t)]^2\, \mathrm{d}t.$$

If $h(\cdot)$ is continuous, then $Th(\cdot)$ is continuous because it is the integral of a continuous function. It is straightforward to show that $Th(q) \in [0,1]$ if $h \in C[0,1]$.

When endowed with the sup norm, $C[0,1]$ is a complete metric space (see Apostol 1974, p. 102, problems 4.66 and 4.67). Furthermore, T as defined is a contraction mapping, that is

$$\sup_q \|Th(q) - Tk(q)\| \le c \sup_q \|h(q) - k(q)\|$$

for some contraction constant $c \in (0,1)$. To establish this, note that

$$\begin{aligned}
Th(q) - Tk(q) = \theta^2 \int_0^\infty \Big[&h\big([(1 - q/\psi) - q^*]\exp\{\eta t\} + q^*\big) \\
&- k\big([(1 - q/\psi) - q^*]\exp\{\eta t\} + q^*\big)\Big] \cdot [1 - G(t)]^2\, \mathrm{d}t.
\end{aligned}$$

It follows that

$$\sup_q \|Th(q) - Tk(q)\| \;\le\; \sup_q \|h(q) - k(q)\| \;\cdot \theta^2 \int_0^\infty [1 - G(t)]^2\, \mathrm{d}t.$$

Moreover, $\int_0^\infty [1-G(t)]^2 \,\mathrm{d}t = 1/(2\theta)$ by (B.4). Hence T is a contraction with contraction constant $c = \theta/2$. Applying the contraction mapping theorem (Apostol 1974, Theorem 4.48, p. 92), we can conclude that the mapping T has a unique fixed point.

Let $\rho(q, 0)$ be the unique fixed point of T. By construction $\rho(q, 0)$ satisfies (B.6). Using (B.5) one can define $\rho(q, t)$ for all t. Integrating over all firms of all ages yields the mass of firms with known-worker share q: $R(q) = \int_0^\infty \rho(q, t)g(t)\,\mathrm{d}t$. Since $\rho(q, t)$ is bounded and continuous, $R(\cdot)$ is well defined and continuous in q. From $R(\cdot)$ one can define the probability density function of the known-worker share across firms with

$$f(q) = \frac{R(q)}{\int_0^1 R(q)\,\mathrm{d}q} = \frac{\int_0^\infty \rho(q, t) \exp\{-\theta t\}\,\mathrm{d}t}{\int_0^1 \int_0^\infty \rho(q, t) \exp\{-\theta t\}\,\mathrm{d}t\,\mathrm{d}q}.$$

Since $R(\cdot)$ is continuous, the density $f(\cdot)$ is well defined whenever $R(q) \neq 0$.

C Departure Hazard Estimates for Parent Workers

Table C.1 reports probability estimates from linear parent-year fixed effects regressions of departure indicators on the set of tenure bin indicators, worker characteristics as in Table 3, the log monthly wage and a constant. The reported estimates are for the results depicted in Figure 1, with standard errors clustered at the parent-year level (in brackets). Column 1 shows the coefficients from the regression of an indicator of departure to a spinoff; those estimates underlying the left panel of Figure 1. Columns 2 and 3 together show coefficients from another single regression, also of an indicator of departure to a spinoff as dependent variable. To preserve space, we show the coefficients of the plain regressors in column 3 and show the coefficients of interaction terms with an indicator for being well networked (at least two preceding occupations at employer) in column 2. The sum of the tenure-bin coefficients in columns 2 and 3 and the coefficient on the well-networked indicator therefore represents the departure hazard to a spinoff for well networked workers by tenure bin, and underlies the dark black dots in the right panel of Figure 1. The coefficients in column 3 alone represent the departure hazard for the less networked by tenure bin, and that prediction underlies the light grey dots in the right panel of Figure 1. The Online Appendix reports results for Figures 2 and 3.

D Quantification

D.1 Calibrating separation rate δ and internal promotion rate ϕp_0

The separation hazard for team members of any tenure with a spinoff firm is constant at $\delta + \theta\gamma$. If the spinoff firm does not have spinoffs of its own, the separation hazard for team members equals δ. Table D.1 is a re-estimate of Table 3 after restricting the sample to spinoffs that do not have spinoffs themselves. For each column, the sum of the coefficient on the team indicator and the retention hazard for non-team workers yields an estimate of $1 - \delta$, the retention hazard for team members. The team indicator is an estimate of the retention hazard gap β. As our estimate of the retention hazard for non-team workers we use the predicted retention rate from all regressors of Table D.1,

Table C.1: DEPARTURE HAZARDS OF PARENT WORKERS TO SPINOFFS

	Parent Workers		
	Fig. 1 left	Fig. 1 right	
Departure indicator		Well netw.	Less netw.
OLS	(1)	(2)	(3)
Tenure 3-6 mo.	-0.0059	0.0017	-0.0057
	(0.0006)***	(0.0007)**	(0.0006)***
Tenure 7-12 mo.	-0.0022	0.0009	-0.002
	(0.0005)***	(0.0006)	(0.0005)***
Tenure 13-18 mo.	-0.0018	0.0011	-0.0018
	(0.0004)***	(0.0005)*	(0.0004)***
Tenure 19-24 mo.	0.0007	-0.0004	0.0009
	(0.0004)	(0.0005)	(0.0005)**
Tenure 25-30 mo.	-0.0005	0.0003	-0.0005
	(0.0004)	(0.0005)	(0.0004)
Tenure 31-36 mo.	0.0006	-0.0006	0.0009
	(0.0004)	(0.0006)	(0.0004)**
Tenure 37-42 mo.	0.0001	-0.0001	0.0002
	(0.0003)	(0.0005)	(0.0004)
Tenure 43-48 mo.	0.0012	-0.0003	0.0013
	(0.0003)***	(0.0005)	(0.0004)***
Tenure 49-60 mo.	0.0003	6.37e-06	0.0003
	(0.0002)	(0.0004)	(0.0003)
Tenure 73-84 mo.	0.0001	-0.0001	0.0002
	(0.0003)	(0.0006)	(0.0003)
Tenure 85-96 mo.	0.0002	-0.001	0.0005
	(0.0003)	(0.0005)**	(0.0004)
Tenure 97-108 mo.	0.0003	-0.0003	0.0004
	(0.0003)	(0.0004)	(0.0004)
Tenure 109-120 mo.	-0.0004	-0.0006	-0.0002
	(0.0003)	(0.0004)	(0.0003)
Tenure 121-144 mo.	-0.0002	-0.0007	4.54e-05
	(0.0003)	(0.0005)	(0.0004)
Tenure 145-168 mo.	-0.0002	-0.0007	-4.75e-06
	(0.0004)	(0.0004)	(0.0005)
Tenure 169-192 mo.	-2.76e-05	-0.0001	-1.93e-05
	(0.0006)	(0.0007)	(0.0005)
Tenure 193-216 mo.	0.0005	0.0002	0.0004
	(0.0008)	(0.0012)	(0.0006)
Tenure 217-240 mo.	-0.0011	-0.0004	-0.0009
	(0.0006)*	(0.0006)	(0.0007)
Tenure $\geq$ 241 mo.	-0.0017	-0.0016	-0.001
	(0.0008)**	(0.0005)***	(0.0007)
Well-networked		0.0012	
		(0.0004)***	

continued

Table C.1: DEPARTURE HAZARDS OF PARENT WORKERS TO SPINOFFS, CONT'D

	Parent Workers		
	Fig. 1 left	Fig. 1 right	
Departure indicator		Well netw.	Less netw.
OLS	(1)	(2)	(3)
continued			
Some High School	-0.0018		-0.0018
	(0.0004)***		(0.0004)***
Some College	-0.0037		-0.0037
	(0.0005)***		(0.0005)***
College degree	-0.0054		-0.0053
	(0.0006)***		(0.0006)***
Pot. lab. force exp.	-0.0011		-0.0012
	(0.0009)		(0.0009)
Sq. Pot. lab. force exp.	0.0015		0.0016
	(0.0005)***		(0.0005)***
Cub. Pot. lab. force exp.	-0.0005		-0.0005
	(0.0001)***		(0.0001)***
Prof./Manag'l. Occ.	0.002		0.0019
	(0.001)**		(0.001)**
Tech'l./Superv. Occ.	-0.001		-0.0011
	(0.0008)		(0.0008)
Unsk. Wh. Coll. Occ.	-0.0014		-0.0015
	(0.0009)*		(0.0009)*
Skld. Bl. Collar Occ.	0.0011		0.0011
	(0.0012)		(0.0012)
Log monthly wage	0.0001		0.0001
	(0.0004)		(0.0004)
Obs.	28,216,587	28,216,587	
R^2	.2687	.2687	
Mean Dep. variable	0.0175	0.0175	
Parent-year panels	43,182	43,182	

Source: RAIS 1995-2001, parent firms 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 MRT. 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 linear parent-year fixed effects regressions. Dependent variable is indicator of departure to spinoff. Coefficients for interactions of female with all other worker characteristics are not shown. 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.

except the team indicator. Table D.2 reports the retention hazard gap β, the retention hazard for non-team workers, and the separation hazard for team members δ for each period $t+1, \ldots, t+6$. We use the average over $t+1, \ldots, t+6$ as the estimate of δ with which to calibrate our model.

Calibration of the internal promotion rate ϕp_0, the rate at which non-team workers of unknown match quality are discovered to be of high match quality, is more involved. We need to know $1 - q_{i0}(\tau)$, the proportion of the non-team worker cohort that was hired at the founding time of firm i and that is of *unknown* match quality when the cohort has tenure τ. From the proof of Proposition 1, we know that the difference between the average retention hazards for team members and non-team workers (the retention hazard gap) equals $\beta \equiv [1-q_{i0}(\tau)][\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]$. This difference is equal to the coefficient on the team indicator in our retention hazard regressions. Since we will use the coefficients from Table D.1, with the sample restricted to spinoffs that have no spinoffs themselves, we can set θ equal to zero for the remaining derivations. Note that, in discrete time, the share of workers employed in the previous year τ who are still employed in the current year $\tau+1$ depends on the share of workers that were of unknown match quality in the previous year τ. We then have:

$$\beta(\tau+1) = [1 - q_{i0}(\tau)](\phi - \phi p_0). \tag{D.1}$$

This equation can be rewritten in terms of growth factors so that the constants ϕ and p_0 drop out:

$$\frac{\beta(\tau+2)}{\beta(\tau+1)} = \frac{1 - q_{i0}(\tau+1)}{1 - q_{i0}(\tau)}. \tag{D.2}$$

As stated in the text, we assume that the share of non-team workers of known match quality is zero at the beginning of the second instead of the first year of operation of the employee spinoff, implying that $1 - q_{i0}(t+1) = 1$. This assumption, combined with the above equation, allows us to infer

$$1 - q_{i0}(\tau+1) = [1 - q_{i0}(\tau)]\beta(\tau+2)/\beta(\tau+1) \tag{D.3}$$

recursively for $\tau+1 = t+2, \ldots, t+5$. Table D.2 shows the results.

Now we rewrite in discrete time the expression for the relative change in the share of known match quality workers from the proof of Lemma 2, and obtain

$$\frac{q_i(\tau+1) - q_i(\tau)}{q_i(\tau)} = \frac{1 - q_i(\tau)}{q_i(\tau)}\,\phi p_0 + [1 - q_i(\tau)]\,(\phi - \phi p_0)$$

after setting θ to zero. Note that this relationship also applies to the non-team worker cohort and its known match-quality share $q_{i0}(\tau)$. Expressing the same relationship in terms of the unknown match-quality share $1 - q_{i0}(\tau)$ yields

$$\frac{[1 - q_{i0}(\tau+1)] - [1 - q_{i0}(\tau)]}{1 - q_{i0}(\tau)} = -\phi + [1 - q_{i0}(\tau)](\phi - \phi p_0)$$

after some manipulation. Using equations (D.1) and (D.2) in that last expression allows us to solve for ϕ in terms of the retention hazard gap:

$$\phi = 1 + \beta(\tau+1) - \frac{\beta(\tau+2)}{\beta(\tau+1)}.$$

Finally, using equation (D.1) allows us to solve for the internal promotion rate ϕp_0 in terms of the retention hazard gap and the unknown match-quality share in the non-team worker cohort:

$$\phi p_0 = \phi - \frac{\beta(\tau+1)}{1 - q_{i0}(\tau)} = 1 + \beta(\tau+1) - \frac{\beta(\tau+2)}{\beta(\tau+1)} - \frac{\beta(\tau+1)}{1 - q_{i0}(\tau)}. \tag{D.4}$$

We can then use our coefficient estimates of β and computations of $[1 - q_{i0}(\tau)]$ to infer ϕp_0. Table D.2 shows the implied values of ϕp_0 for each of the periods $t+1, \ldots, t+4$. We use the average over $t+1, \ldots, t+4$ as the estimate of ϕp_0 with which we calibrate our model.

D.2 Calibrating the steady-state proportion of known match quality $\bar{q}$ with and without social capital

Table D.3 plugs the estimates of δ and ϕp_0 from Table D.2 along with $q(0)_{spin} = 0.489$ (the observed initial share of workers of known match quality at spinoffs in our data) into equations (19) and (20) to compute $q(t)_{\alpha=0}$, $q(t)_{spin}$, and $q(t)_{agg} = 0.29q(t)_{spin} + 0.71q(t)_{\alpha=0}$. (29 percent of new Brazilian firms in our data are employee spinoffs.) We then compute the employment-weighted averages of $q(t)_{\alpha=0}$ and $q(t)_{agg}$ to obtain our estimates of $\bar{q}_{\alpha=0}$ and $\bar{q}$, respectively.

In order to compute employment in Brazil's domestically owned private sector by firm age, we use the years in which firms in this sector first appeared in RAIS as their birth years. Since our data begin in 1986, it is impossible to determine when firms that first appear in 1986 were born. Given our focus on the period 1995-2001, this will be a problem for all firms that are more than eight years old in 1995. We therefore aggregate all firms older than eight years, regardless of cohort, into one category, age 9+. We assign that category the steady state value q^* of the share of workers of known match quality. As can be seen from Table D.3, this has very little effect on our estimates of $\bar{q}_{\alpha=0}$ and $\bar{q}$ given the rate at which both $q(t)_{\alpha=0}$ and $q(t)_{spin}$ converge to q^*. What little effect is present works to reduce our estimate of the impact of social capital since $\bar{q}_{\alpha=0}$ is raised more than $\bar{q}$.

The last column of Table D.3 shows the cumulative contribution to the difference between $\bar{q}$ and $\bar{q}_{\alpha=0}$ of employment in firms of age less than or equal to the age for each row of the table. Roughly one-third of the total difference is attributable to new firms, and over 90 percent of the difference comes from firms four years old or younger.

Table D.1: RETENTION HAZARD GAP AT SPINOFF (EXCLUDING SPINOFFS WITH SPINOFFS)

	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	0.0706	0.1072	0.0619	0.0463	0.0393	0.0265
	(.0019)***	(.0018)***	(.0018)***	(.0024)***	(.0032)***	(.0056)***
Some High School	0.0195	0.0195	0.0172	0.0088	0.0076	0.0016
	(.0016)***	(.0024)***	(.0032)***	(.0049)*	(.0066)	(.0112)
Some College	0.0128	0.0054	0.0134	-0.0017	0.0038	0.0648
	(.0036)***	(.0062)	(.0070)*	(.0102)	(.0162)	(.0489)
College Degree	0.0131	0.0133	0.0120	-0.0008	0.0013	0.0282
	(.0033)***	(.0054)**	(.0063)*	(.0087)	(.0115)	(.0338)
Pot. lab. force exp.	-0.0051	-0.0022	0.0050	0.0060	0.0032	0.0090
	(.0006)***	(.0009)**	(.0013)***	(.0019)***	(.0028)	(.0051)*
Sq. Pot. lab. force exp.	0.0003	0.0003	-0.0001	-0.0002	-0.00009	-0.0003
	(.00004)***	(.00006)***	(.00009)	(.0001)	(.0002)	(.0004)
Cub. Pot. lab. force exp.	-6.68e-06	-7.91e-06	1.38e-06	1.43e-06	1.35e-06	3.52e-06
	(1.17e-06)***	(1.62e-06)***	(2.44e-06)	(3.44e-06)	(4.82e-06)	(9.74e-06)
Qrt. Pot. lab. force exp.	4.38e-08	5.87e-08	-1.38e-08	-6.79e-09	-1.71e-08	-1.29e-08
	(1.04e-08)***	(1.41e-08)***	(2.18e-08)	(3.04e-08)	(4.20e-08)	(8.22e-08)
Female employee	-0.0150	-0.0165	-0.0030	-0.0150	-0.0338	0.0332
	(.0045)***	(.0070)**	(.0102)	(.0154)	(.0228)	(.0359)
Obs.	1,211,016	635,326	285,350	126,685	51,615	19,221
R^2	.258	.249	.236	.26	.283	.245
Mean Dep. variable	.761	.669	.764	.797	.821	.826
Firm panels	69,513	47,246	26,408	14,114	6,296	2,367

Source: RAIS 1995-2001, employee spinoff firms with at least one non-team member at time of entry; excluding from sample spinoffs that have other spinoffs.
Notes: Replication of Table 3 for sample of spinoffs that do not have other spinoffs. Definition of employee spinoff (quarter-workforce criterion) as described in MRT. Coefficients for interactions of female with all other worker characteristics are not shown. 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 D.2: PARAMETER ESTIMATES

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	Average
Retention hazard gap β	0.0706	0.1072	0.0619	0.0463	0.0393	0.0265	
Non-team worker retention hazard rate	0.7237	0.6100	0.7264	0.7682	0.7971	0.8096	
Team-member separation rate δ	0.2057	0.2828	0.2117	0.1855	0.1636	0.1639	0.2022
Unknown match qual. sh. $1 - q_{i0}$	1	0.5770	0.4321	0.3662	0.2470		
Internal promotion rate ϕp_0	0.4230	0.2058	0.0917	0.2575			0.2445

Notes: The retention hazard gap β is the coefficient estimate for the team members indicator in the retention regression in Table D.1 (first row). The non-team worker retention hazard is the predicted retention rate from all regressors of Table D.1, except the team indicator. The separation rate δ is one less the sum of β and the predicted non-team worker retention hazard. The share of unknown match quality in a non-team worker cohort $1 - q_{i0}$ is 1 at $t+1$ by convention and follows equation (D.3) with firm age. The internal promotion rate ϕp_0 follows from equation (D.4).

Table D.3: CALIBRATION OF $\bar{q}$ AND $\bar{q}_{\alpha=0}$

Firm age	Employment Share	Average Firm Size	$q(t)_{spin}$	$q(t)_{\alpha=0}$	$q(t)_{agg}$	Cumulative Contribution to $\bar{q} - \bar{q}_{\alpha=0}$
0	0.0386	13.73	0.4890	0	0.1418	0.0055
1	0.0460	13.03	0.5100	0.1972	0.2879	0.0096
2	0.0447	14.24	0.5235	0.3233	0.3814	0.0122
3	0.0408	14.86	0.5321	0.4040	0.4412	0.0138
4	0.0370	15.51	0.5376	0.4557	0.4794	0.0146
5	0.0335	16.23	0.5411	0.4887	0.5039	0.0151
6	0.0309	16.74	0.5433	0.5098	0.5195	0.0154
7	0.0287	17.26	0.5448	0.5233	0.5295	0.0156
8	0.0282	18.22	0.5457	0.5320	0.5360	0.0157
9+	0.6717	43.90	0.5473	0.5473	0.5473	0.0157
Employment-weighted average			0.5409	0.4866	0.5023	0.0157

Notes: Estimates of $q(t)_{spin}$, $q(t)_{\alpha=0}$ and $q(t)_{agg} = 0.29q(t)_{spin} + 0.71q(t)_{\alpha=0}$ based on equations (19) and (20) using δ and ϕp_0 from Table D.2 along with $q(0)_{spin} = 0.489$. Age and employment from RAIS 1986-2001.

References

ABOWD, J. M., F. KRAMARZ, D. N. MARGOLIS, AND K. R. TROSKE (2001): "The Relative Importance of Employer and Employee Effects on Compensation: A Comparison of France and the United States," *Journal of the Japanese and International Economies*, 15(4), 419–436.

ANTON, J. J., AND D. A. YAO (1995): "Start-ups, Spin-offs, and Internal Projects," *Journal of Law, Economics, & Organization*, 11(2), 362–378.

APOSTOL, T. M. (1974): *Mathematical analysis*. Addison-Wesley, Reading, Mass., 2nd edn.

BANDIERA, O., I. BARANKAY, AND I. RASUL (2008): "Social Capital in the Workplace: Evidence on its Formation and Consequences," *Labour Economics*, 15(4), 724–748.

——— (2009): "Social Connections and Incentives in the Workplace: Evidence From Personnel Data," *Econometrica*, 77(4), 1047–1094.

——— (2010): "Social Incentives in the Workplace," *Review of Economic Studies*, 77(2), 417–458.

DE NEGRI, J. A., P. FURTADO, N. R. D. SOUZA, AND J. S. ARBACHE (1998): "Mercado Formal de Trabalho: Comparação entre os microdados da RAIS e da PNAD," *IPEA Texto para Discussão*, 840, Instituto de Pesquisa Econômica Aplicada, Rio de Janeiro.

EISENHARDT, K. M., AND C. B. SCHOONHOVEN (1990): "Organizational Growth: Linking Founding Team, Strategy, Environment, and Growth Among U.S. Semiconductor Ventures, 1978-1988," *Administrative Science Quarterly*, 35(3), 504–529.

ERIKSSON, T., AND J. M. KUHN (2006): "Firm Spin-Offs in Denmark 1981-2000: Patterns of Entry and Exit," *International Journal of Industrial Organization*, 24(5), 1021–1040.

FARBER, H. S. (1999): "Mobility and Stability: The Dynamics of Job Change in Labor Markets," in *Handbook of labor economics*, ed. by O. Ashenfelter, and D. Card, vol. 3B, pp. 2439–83. Elsevier Science, North-Holland, Amsterdam, New York and Oxford.

FRANCO, A. M., AND D. FILSON (2006): "Spin-Outs: Knowledge Diffusion through Employee Mobility," *RAND Journal of Economics*, 37(4), 841–860.

HENDERSON, R. M., AND K. B. CLARK (1990): "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms," *Administrative Science Quarterly*, 35(1), 9–30.

HOLMSTROM, B. (1982): "Moral Hazard in Teams," *Bell Journal of Economics*, 13(2), 324–340.

JOVANOVIC, B. (1979): "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 87(5), 972–990.

KLEPPER, S. (2001): "Employee Startups in High-Tech Industries," *Industrial and Corporate Change*, 10(3), 639–74.

KLEPPER, S., AND S. SLEEPER (2005): "Entry by Spinoffs," *Management Science*, 51(8), 1291–1306.

LANCASTER, K. J. (1966): "A New Approach to Consumer Theory," *Journal of Political Economy*, 74(2), 132–157.

LAZEAR, E. P. (2003): "Firm-specific Human Capital: A Skill-Weights Approach," *NBER Working Paper*, 9679.

MAS, A., AND E. MORETTI (2009): "Peers at Work," *American Economic Review*, 99(1), 112–145.

MENEZES-FILHO, N. A., M.-A. MUENDLER, AND G. RAMEY (2008): "The Structure of Worker Compensation in Brazil, with a Comparison to France and the United States," *Review of Economics and Statistics*, 90(2), 324–346.

MOSCARINI, G. (2005): "Job Matching and the Wage Distribution," *Econometrica*, 73(2), 481–516.

MUENDLER, M.-A., AND J. E. RAUCH (2011): "Employee Spinoffs, Market Cannibalization, and Agglomeration: Evidence from Brazil," University of California, San Diego, unpublished manuscript.

MUENDLER, M.-A., J. E. RAUCH, AND O. TOCOIAN (2012): "Employee Spinoffs and Other Entrants: Stylized Facts from Brazil," *International Journal of Industrial Organization*, 30(5), 447–458.

PHILLIPS, D. J. (2002): "A Genealogical Approach to Organizational Life or Chances: The Parent-progeny Transfer Among Silicon Valley Law Firms, 1946-1996," *Administrative Science Quarterly*, 47(3), 474–506.

ROTEMBERG, J. J. (1994): "Human Relations in the Workplace," *Journal of Political Economy*, 102(4), 684–717.

TUSHMAN, M. L., AND P. ANDERSON (1986): "Technological Discontinuities and Organizational Environments," *Administrative Science Quarterly*, 31(3), 439–465.