Mobilizing Social Capital Through Employee Spinoffs*

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Abstract

Founding teams of new firms frequently come from a common employer. We model the formation of founding teams and the entry of their new firms—employee spinoffs—by extending the theory of job matching and employer learning to learning also among employees. Employees build social capital as they learn about their colleagues' suitable characteristics to start a 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, most notably, that this difference shrinks with worker tenure at the firm. For parent firms, a version of 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 the canonical employer learning model. 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.

Keywords: Employee spinoffs; entrepreneurship; labor turnover; firm performance; learning; social capital

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1 Introduction

Like a city, a firm brings together people in ways both planned and unplanned. A firm allows its employees to learn about each other's abilities and preferences. This co-worker information is a form of *social capital* that can prove useful to one or more employees who has an idea that is best exploited at a new firm. The worker-entrepreneurs can try to lure away those of their co-workers who they believe will be most productive in the newly formed *employee spinoff*. We refer to the worker-entrepreneurs and those of their colleagues who jointly depart from the parent firm to the employee spinoff as the *founding team*.[1] Founding teams mobilize social capital because co-worker information would remain unutilized at parents but social capital informs recruitment for the spinoff. Employee spinoffs thus act as vehicles that raise the quality of matches between workers and firms.

How does a spinoff's workforce form? To model recruitment and retention, we extend the Jovanovic (1979) theory of job matching and worker turnover to allow employees to build social capital: employees learn about their colleagues' abilities and preferences initially faster than the employer. Social capital in our model gives the founding team members confidence in their match with an entrepreneur's idea so that they leave their parent-firm jobs to join the new enterprise. Social capital also gives the entrepreneur confidence that the workers in the founding team will be better matches than typical job applicants from outside. To derive testable and quantifiable predictions, we use the Moscarini (2005) version of the Jovanovic theory for a continuum of firms and workers, and adopt two important extensions. We allow firms to employ multiple employees so that there can be social learning, and we introduce spinoff entry under an exogenous rate of idea generation. The model explains the microeconomics behind employment dynamics at parents and spinoffs, and presents empirical implications.

We use comprehensive linked employer-employee data to capture the relevance of spinoffs across all sectors of the economy. Brazilian employer-employee records for the universe of formal firms offer extensive coverage and essential information to identify employee spinoffs (we implement spinoff definitions from Muendler, Rauch, and Tocoian 2012). The key predictions

[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 formation of founding teams rather than in the incentives used to elicit output from a given team.

of our model concern differences between employees inside a firm, so all our empirical results are based on within-firm estimates conditional on spinoff or parent fixed effects. For the spinoff workforce, our model predicts that spinoffs retain founding team members at a higher frequency than they retain other workers with no previous parent employment, because spinoff employers know the match quality of founding team members but only learn about the match quality of outside hires over time. Moreover, the model predicts that the gap in retention rates and a related gap in wages gradually close as spinoff employers learn about the match quality of the outside hires. These predictions are strongly supported in Brazilian data for the period 1995-2001. For the parent workforce, a version of our model implies that the departure rate at which a parent employee leaves to join a spinoff initially increases with tenure at the parent, because the worker-entrepreneurs learn about match quality faster than the parent employer. On the other hand, the departure probability that an employee quits to leave for a spinoff eventually decreases with tenure at the employer, because only employees who are well matched to the parent remain over time and they do not depart for spinoffs. This inverted U in the probability of departure to a spinoff as a function of tenure at the parent contrasts sharply with the common prediction of labor-market and matching models that the probability of separation monotonically declines with tenure. Our Brazilian data for the period 1995-2001 confirm the common result that separation rates decline with tenure for job-to-job transitions in general. However, the estimated probability of departure to spinoff employment in particular exhibits an inverted-U shape as a function of tenure at the parent, just as our model predicts.

The dynamics of our model are critical to understanding the role of social capital in workforce formation. Our theoretical results are also essential to evaluating the quantitative impact of spinoffs and their social capital on the economy-wide match quality between workers and firms. We derive the equilibrium distributions of firm age and match qualities, as they depend on rates of learning and worker turnover in the model. The effect of social capital on firm output is at its maximum at a spinoff's startup, when the spinoff employers have yet to learn about the match quality of the workers hired from outside. After startup, the rate at which the effect of social capital decays depends on the rates of employer learning as well as endogenous and exogenous worker turnover. Our fully specified dynamic model allows us to calibrate this rate of decay using our estimation results from comparisons between founding team members and other workers within spinoffs and parents. Our model only permits social capital to influence aggregate output through changes in the share of workers known to be of high match quality at new firms.

In a quantification exercise, we combine calibrated retention and departure rates with the firm age distribution and the share of new firms that are employee spinoffs. This yields the conservative 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. Note that this estimate is deliberately narrow to precisely capture only the annual return to spinoff-mobilized social capital shared with the founding team members. The estimate excludes the contribution of social capital to the entry rate of new firms and excludes the earnings that accrue to the spinoff owners. In our conservative approach, the only value of social capital is to improve the matches between workers and firms, and the returns from social capital accrue entirely to the founding team members after they move from the parent to the spinoff. We acknowledge that a connection may exist between team characteristics and spinoff performance as measured, for instance, by firm survival or growth (e.g. Eisenhardt and Schoonhoven 1990, Phillips 2002), but it is difficult to rigorously quantify such a connection when one can argue that worker-entrepreneurs with a better idea can attract a better founding team. We therefore limit our quantitative exercise to the effects of well identified worker moves. Our approach nevertheless holds potential implications for future research into determinants of spinoff and parent performance. For example, parents with more conducive environments for social capital formation might be expected to spawn more successful spinoffs. Similarly, parents with team setups that permit relatively faster employer learning might be expected to retain their able workforces longer and launch more innovations in house.

Differences between firms have been the main subject of the substantial literature on employee spinoffs. Klepper and Sleeper (2005) and Franco and Filson (2006) predict which firms will become parents; Cabral and Wang (2008) and Muendler, Rauch, and Tocoian (2012) compare performance between spinoffs and other entrants; Anton and Yao (1995) explain when employees leave to form their own firms rather than implement their ideas in their current firms. Our novel empirical approach, in contrast, makes comparisons within firms but between founding-team members and other workers to explain how founding teams emerge.

Inasmuch as spinoff entrepreneurs can be seen as "referring" parent employees to their own planned firms, our paper is related to the large literature on worker referrals among existing firms (for recent surveys see, e.g., Ioannides and Loury 2004, Topa 2011).[2] For instance, our findings

[2] Social capital also matters for other aspects of entrepreneurship. Nanda and Sørensen (2010) and Munshi (2011), for example, study the impact of social ties on entry into entrepreneurship rather than recruitment into jobs. En-

on retentions at spinoffs resemble previous evidence in Simon and Warner (1992), who document facts consistent with the idea that referrals from current employees are more informative about match quality than direct applications or applications through intermediaries. Recent papers by Brown, Setren, and Topa (2016), Burks, Cowgill, Hoffman, and Housman (2015) and Dustmann, Glitz, Schönberg, and Brücker (2015) update, confirm and extend the earlier findings by Simon and Warner (1992). We discern parent and spinoff firms, and offer a model to assess founding team formation. Our framework and estimation strategy allow us to track the economic conditions of spinoff recruitment and to quantify the aggregate impact of related social capital.

Our paper is also related to the literature that investigates the impact of social relationships on performance of workers within a given firm (e.g. Rotemberg 1994, Mas and Moretti 2009). This literature offers a rich menu of theories that show how repeated interactions among workers, or other-regarding preferences, generate high or low worker effort, and tests these theories using a variety of appropriate data. The models and evidence concern static outcomes in existing firms rather than the formation of new firms. Our paper introduces the dynamics of spinoff entry, worker mobility between firms, and employment turnover. Of particular interest is the work by Bandiera, Barankay, and Rasul (2008, 2009, 2010), who investigate the impact of pre-existing ties on worker performance. Those relationships are relevant to our investigation insofar as the social ties that facilitated recruitment from the parent may persist among the founding-team members. If ties lead team members to exert higher effort, their job performance could provide an alternative explanation for why their turnover at spinoffs is lower. That alternative hypothesis in fact highlights the crucial role of learning for the dynamics in our model. The posited alternative explanation does not predict that the team member retention rate gap declines monotonically with tenure at the spinoff, nor that the probability of departure from the parent to the spinoff eventually declines.

Two additional alternative hypotheses, closely related to each other, are (i) that a spinoff entrepreneur recruits from the parent those employees who have generically high ability, and (ii) that former parent employees transfer relevant firm-specific human capital to spinoffs. Both additional hypotheses can capture the dynamics of the team member retention rate gap at spinoffs: the gap closes as low-ability outside hires are weeded out, or outside hires catch up in accumulation of firm-specific human capital.[3] To test the first additional hypothesis we use the idea that high ability

trepreneurs can also use social ties to further their young businesses in the product market (e.g., McMillan and Woodruff 1999, Fafchamps and Minten 2002).

[3]However, the correspondence between our retention rate gap results and those in the referral literature cited above are at variance with the second hypothesis, since referrers should have no advantage over their employers in finding

workers should have had high wages at their previous employers, controlling for their observable characteristics and an overall plant effect. We indeed find that workers with high Mincer wage residuals net of plant effects at their previous employers tend to be retained more at spinoffs, and that this effect is larger for workers who came from the parent firm. To test the second additional hypothesis we use tenure at the previous employer as a proxy for accumulation of firm-specific human capital. We find that tenure at previous employers in general, though not specifically at parent firms, is strongly associated with retention at spinoffs. Yet controlling for those variables does not substantively change our results for the team member retention rate gap. We therefore view those additional hypotheses as complementary to our assessment of founding team formation.

In the next section we develop our model of employee spinoffs and how they mobilize social capital. Section 3 describes our data and the identification of spinoff firms. Our results on spinoff workers are presented in Section 4, where we compare retention rates and wages between founding team members and a spinoff's other hires. Our results for parent-firm workers follow in Section 5, where we compare the tenure of workers who depart for spinoffs to that of workers who do not. We use the estimates to calibrate our model and quantify 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.[4] 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

applicants from firms that generate relevant firm-specific human capital.

[4]We retain the convention from Jovanovic (1979) and Moscarini (2005) that firms do not vary in size.

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 (Tushman and Anderson 1986, Henderson and Clark 1990). 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. This co-worker learning is different in nature from employer learning in that it results from direct observations of a colleague's abilities and preferences rather than from inferences based on 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. For example, creativity and speed are important both in academia and consulting, but with different weights. A professor who hires a junior colleague for his consulting firm will not give his Dean cause to promote that colleague. 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). As mentioned in the Introduction, 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.[5] 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.[6] 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 test the relevance of the alternative hypothesis in our empirical work.

2.2 Employer learning

To make room for our extensions, we radically simplify the Jovanovic (1979) model of employer learning. Following Moscarini (2005) we allow match quality to take on only two values, high and low. A high-quality match produces a flow of output μ_H 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 whose match quality is known to firm i when the firm has age t.

Let us provisionally assume that an employee separates from the firm as soon as the match is revealed to be low quality (for the derivation of endogenous quits see below). Then output $x_i(t)$

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

[6] 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.

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 (1979) 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.[7] There is no forgetting, so an employee's wage at a given firm i weakly rises over time. Note that, as in Jovanovic (1979), the increased wage and retention of an employee provide no information to other potential employers about the worker's productivity in their firms. Match quality is firm-worker specific.

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 separation δ are constant. For a cohort of workers who are still employed at the same firm, however, the fraction with known match quality strictly increases with tenure because workers with revealed match quality quit if and only if their match has low quality. It follows that a cohort's average wage strictly increases with tenure, and that its average hazard rate of separation strictly decreases because the rate of endogenous quitting falls as the fraction of workers with known match quality in the cohort increases. We summarize these findings in a lemma. In this lemma and throughout the remainder of the paper we use the average hazard rate of retention (equals one

[7] 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 Subsection 2.5 and Appendix A).

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. 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. □

The lemma extends the results of Jovanovic (1979) that are most important for our purposes. We now turn to employee spinoff firms and the process by which they form.

2.3 Spinoff entrepreneurship and 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 the complementary probability one-half the shock is severe and results in firm exit. Hence spinoffs enter 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 equivalent to 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. However, 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 a partner's social network predates her idea for a new firm, she cannot select colleagues to be in her network based on their match quality with her new firm. Thus, when her idea arrives, the probability that a member of her 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.[8] 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 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. 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

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

The result that the average cohort wage strictly increases with tenure follows similarly to Lemma 1. The average hazard rate of retention of the cohort is now $q_i(\tau)(1-\delta-\theta\gamma) + [1-$

[8] 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.

$q_i(\tau)][1-\delta-\theta\gamma-\phi(1-p_0)-\theta(1-\gamma)\alpha p_0] = 1-\delta-\theta\gamma - [1-q_i(\tau)][\phi(1-p_0)+\theta(1-\gamma)\alpha p_0]$. Since $q_i(\tau)$ strictly increases with tenure, the cohort average hazard rate of retention strictly increases with tenure as well. □

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 augments the cohort of workers with known match quality and the latter learning process removes workers of unknown match quality from the cohort at the parent.

Having extended our model of learning at the parent firm, we now consider the spinoff firm. Like any firm, the spinoff employs a unit mass of employees in total. To complement the founding team, the spinoff firm 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.[9] 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 individual worker dynamics. In our data, workers leave the formal sector for informal work, self employment or unemployment, so we allow for a status outside formal work. As in Moscarini (2005), an 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.

In equilibrium, the flow value a from implementing a spinoff idea and the flow value b of unemployment must satisfy certain parameter restrictions. First, an individual's value of being a spinoff partner must exceed the value of employment under known match quality so that a group of workers will depart and become spinoff partners when an according innovation shock hits an incumbent firm. This requirement places a lower bound on the parameter a. Second, an individual's value of employment under unknown match quality must exceed the value of unemployment so that a worker will accept a new job when one becomes available. Third, the value of unemployment must be large enough so that an employee prefers to quit his current job when he is poorly

[9] 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.

matched. The latter two requirements place an upper and a lower bound on the parameter b. In Appendix A, we derive the solutions for the value functions of employment under unknown and known match quality, unemployment, and partnership at a spinoff, and we present the natural restrictions on the flow values a and b to satisfy the required equilibrium dynamics. The job finding rate λ in turn is determined in equilibrium so that the flow of employees out of unemployment equals the flow into unemployment, and we derive the job finding rate in Subsection 2.5.

2.4 Firm dynamics

We have seen that the ability of spinoff entrepreneurs to mobilize social capital for their new firm depends negatively on the proportion of their colleagues whose match quality with the current employer is known. We now show how the proportion of workers with known match quality $q_i(t)$ 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 $q_i(t)\,\delta + q_i(t)\,\theta\gamma$.[10] It follows that the change in the fraction of workers with known match quality is

$$\dot{q}_i(t) = [1-q_i(t)]\,\phi p_0 - q_i(t)\,(\delta + \theta\gamma), \tag{3}$$

which 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

$$q^* = \frac{\phi p_0}{\delta + \theta\gamma + \phi p_0}. \tag{4}$$

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

[10] 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.

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 result 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 (3) is a linear first-order non-homogeneous differential equation. Its solution can be written

$$q_i(t) - q^* = C_{i0} \exp\{-(\delta + \theta\gamma + \phi p_0)t\}, \tag{5}$$

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 i spins off.[11] It follows that a spinoff i's initial share $q_i(0)$ of employees with known match quality is given by

$$q_i(0) = [1 - q_p(t_{i0})](1-\gamma)\alpha p_0. \tag{6}$$

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 (6) in (5), we find the evolution of the spinoff's share of employees with known quality at firm age t

$$q_i(t) - q^* = \{[1 - q_p(t_{i0})](1-\gamma)\alpha p_0 - q^*\} \exp\{-(\delta + \theta\gamma + \phi p_0)t\}. \tag{7}$$

2.5 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

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

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

$$\lambda = \delta + \theta(1{+}\gamma) + \phi(1{-}p_0)(1{-}\bar{q}). \tag{8}$$

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 in turn implies a stationary value of λ by (8). The following property of our model guarantees existence.

Theorem 1. *The probability density function $f(q)$, which measures the frequency of firms with a share q of workers with known match quality in steady-state equilibrium, exists and is continuous.*

Proof. See Appendix B. □

The share of workers with known match quality q is bounded between zero and one. Therefore, the existence of a steady-state continuous probability density function $f(q)$ for the population of firms by Theorem 1 implies that the economy-wide fraction of employees with known match quality $\bar{q}$ in steady-state equilibrium exists. Hence, λ exists as given by (8).

3 Data and Identification of Employee Spinoffs

Our data derive from the linked employer-employee records RAIS (*Relação Anual de Informações Sociais* of the Brazilian labor ministry *MTE*), which record comprehensive individual employee information on occupations, demographic characteristics and earnings, along with employer identifiers. By Brazilian law, every private or public-sector employer must report this information every year.[12] De Negri, Furtado, Souza, and Arbache (1998) compare labor force information in RAIS

[12]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.

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 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 firm'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.[13] However, if this new firm absorbed at least seventy percent of the workers in one of the parent's plants and has a legal form such that it could be owned and sold by the parent, MRT classify it as a divestiture (an employer-initiated spinoff) rather than an employee spinoff.[14] 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 among employee spinoffs than among new firms without parents but smaller than among divestitures; subsequent exit rates (controlling for size at entry) for employee spinoffs are smaller than for new firms without parents but larger than for divestitures. We will use MRT's criteria to distinguish employee spinoffs from new firms without parents and from divestitures. By those 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.

Spinoffs are ubiquitous and occur with frequencies that broadly reflect the distribution of existing firms (for details see Online Supplement F). Employee spinoffs are founded slightly more frequently than existing firms in the high-tech manufacturing sector and in knowledge-intensive services. The sector with the relatively least frequent entry of spinoffs compared to existing firms is the commerce and hospitality industry (hotels and restaurants). Spinoffs occur particularly frequently compared to existing firms in construction, real estate and business services, and the manufacture of wood, metal products, and chemicals. The occupational profiles at the employee

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

[14] An existing firm that divests itself of one or more plants or divisions creates a (legally new) firm that is likely to satisfy the spinoff criterion based on the fraction of transferring workers. However, the quality of the Brazilian employer-employee data helps us avert a potential misclassification of divestitures as spinoffs. Information on the firm's legal form (*natureza juridica*) and the separate identification of plants within firms are of critical help. By Brazilian commercial law, there are two broad categories of legal form: incorporated firms, and associations or partnerships without independent legal existence. Most important for our purposes, associations or partnerships cannot be owned by companies, but only by physical persons. Therefore, if an employee spinoff is an association or partnership ("non-incorporated" legal forms), it cannot be a divestiture. In contrast, some spinoffs that are incorporated as Public corporation under private control, Non-public corporation, or Limited liability company might be divestitures ("incorporated" legal forms). Inverting the common criterion in the labor literature that a mass layoff is a reduction of the existing workforce by 30 percent or more (e.g. Jacobson, LaLonde, and Sullivan 1993), MRT label a new firm a divestiture if its *natureza juridica* is for an "incorporated" legal form (or if it has unknown legal form) and if it absorbs 70 percent or more of the employees of a plant of an existing firm. MRT also use an alternative 80 percent cutoff, following Benedetto, Haltiwanger, Lane, and McKinney (2007), and show that results are not sensitive to that change. Adopting the conventions from MRT, in this paper we exclude from our spinoff sample the incorporated new firms that absorb a fraction of 70 percent or more of the workforce of an existing firm's plant. We do classify 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 as a spinoff. However, our empirical results are robust to dropping such spinoffs.

spinoffs (for details see Online Supplement F) and at the previous employers before workers joined the employee spinoffs (Table 2) show that team workers take more skill intensive positions, both within the white-collar and within the blue-collar occupation groups. Starting with Table 3, we will be careful to control for this fact in the regressions that we use to test the predictions of our model.

4 Retention Hazards and Wages at Spinoffs

We now turn to empirical tests of our model's predictions for employment and wages 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 establish 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. Similarly, the wage premium Δw between team members and non-team workers at time of hiring is positive and diminishes with cohort tenure.*

Proof. Define $q_{i0}(\tau)$ as the share 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.

The wage of a team member is $w(1)$ at any tenure. Given the share $q_{i0}(\tau)$ of workers in the non-team worker cohort who were hired at the founding time of firm i and who are of known match quality when the cohort has tenure τ, the average wage of the non-team worker cohort is $q_{i0}(\tau)w(1) + [1{-}q_{i0}(\tau)]w(p_0) = w(p_0) + q_{i0}(\tau)[w(1){-}w(p_0)]$. The wage premium between team

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 five, ** one percent.

members and non-team workers at tenure τ is therefore

$$\Delta w = [1 - q_{i0}(\tau)][w(1) - w(p_0)] > 0$$

and diminishes with cohort tenure because $\dot{q}_{i0}(\tau) > 0$. □

The hazard gap β arises because an entrepreneur learns about the match quality of a non-team worker only gradually. In contrast, consider an alternative world with perfect information. Even though it is unlikely that an entrepreneur would find the best workers for her new firm among the few employees at her current employer, an entrepreneur might nevertheless choose those workers to conserve on upfront hiring costs and subsequently replace them with workers who are better fits as her firm matures. In such a world of instantaneous knowledge, Proposition 1 would fail.[15]

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.

To start, we split the workforce of spinoffs into two groups at the time of the spinoff's founding: team members and non-team workers. For each worker group we compute the proportion of

[15] Muendler and Rauch (2011) present evidence that, when locating customers and inputs, spinoff firms remain geographically closer to their parents than new plants that a parent sets up within the firm. That finding is consistent with a new firm's desire to reduce hiring costs by recruiting from the parent.

workers who the spinoff firm retains from one year to the next. Table 1 shows linear regressions where the dependent variable is the proportion of retained workers within each group.[16] Note that all these employees joined the new firm in the same year. The key explanatory variable is an indicator for team members.[17] 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 among 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 job spell at the previous employer are retained more frequently than non-team members, but as the spinoff partners learn about the match quality of non-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 columns 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 short-run 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

[16] Our model applies to permanent rather than temporary separation, so 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.

[17] 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.

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.[18]

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.[19] 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.[20] The previous employers of team members were parent firms, but non-team workers cannot necessarily be tracked to previous formal 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 employment. For trackable workers, we add an indicator for whether their previous employer was in the same 4-digit *CNAE* industry as the spinoff firm. Finally, also for trackable workers, we add a measure of actual, relevant

[18]Farber (1999, pp. 2463-2464) provides an 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."

[19]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.

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

experience (as opposed to potential experience): the log number of months worked at the previous employer.

Table 2 reports the mean values of the control characteristics for team members, trackable non-team workers, and all non-team workers. 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. 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 4-digit *CNAE* industry as the spinoff firm and they have greater tenure with 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. Moreover, as mentioned in the Introduction, the reduction of the retention hazard gap with tenure predicted by Proposition 1 could be explained by non-team workers catching up to team workers in relevant experience.[21]

Tables 3 and 4 repeat the retention hazard regressions of Table 1 at the individual worker 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 the previous job in the same industry has a positive and statistically significant association with retention hazards that follows the same time pattern as the coefficient on the team member indicator, supporting the additional alternative hypothesis mentioned in our Introduction that team members bring firm-specific human capital with them from the parent. Relative to Table 1, the coefficients on team member are reduced by about 10 percent in periods $t+1$ and $t+2$, about 20 percent in periods $t+3$ and $t+4$ and about 30 percent in period $t+5$, before increasing slightly in period $t+6$.[22]

[21] 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.)

[22] This slight increase appears to be driven by the "wrong" sign on the same *CNAE* indicator in period $t+6$. Dropping this variable leaves the coefficients on the team indicator largely unchanged relative to Table 4 except for the

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

	Employees in		
	Team (1)	Nonteam trackable (2)	Nonteam all (3)
Pot. lab. force exp.	20.109 (.012)	18.568 (.014)	16.631 (.012)
Middle School or less	.623 (.0005)	.653 (.0006)	.654 (.0005)
Some High School	.274 (.0005)	.259 (.0006)	.270 (.0005)
Some College	.030 (.0002)	.027 (.0002)	.026 (.0002)
College Degree	.072 (.0003)	.060 (.0003)	.050 (.0002)
Prev. Prof./Manag'l. Occ.	.133 (.0003)	.100 (.0004)	
Prev. Tech'l./Superv. Occ.	.175 (.0004)	.177 (.0005)	
Prev. Unsk. Wh. Coll. Occ.	.161 (.0004)	.168 (.0005)	
Prev. Skld. Bl. Collar Occ.	.401 (.0005)	.404 (.0006)	
Prev. Unsk. Bl. Collar Occ.	.130 (.0003)	.150 (.0005)	
Same *CNAE*	.588 (.0005)	.193 (.0006)	
Prev. Log months of tenure	3.118 (.001)	2.581 (.001)	
Female employee	.293 (.0005)	.269 (.0006)	.302 (.0005)
Observations	974,708	598,565	842,032

Source: RAIS 1995-2001, workers at employee spinoff firms in the founding year.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in MRT. Potential labor force experience equals age minus years of education. Previous occupations are those at 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 previous occupation: Team 19,820, trackable non-team 21,746. Missing data for previous tenure: Team 42,372, trackable non-team 88,970. Missing data for same industry: Team 42,372, trackable non-team 88,970. Missing data for previous log months of tenure and for female: none. Standard errors in parentheses.

Table 3: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, ALL WORKERS

Retention indicator OLS	$t+1$ (1)	$t+2$ (2)	$t+3$ (3)	$t+4$ (4)	$t+5$ (5)	$t+6$ (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 five, ** one percent.

In summary, support for Proposition 1 remains strong.

We can refine the additional alternative hypothesis to focus on actual, relevant experience at the parent firm in particular as opposed to the previous employer in general. 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. We therefore add the interaction of the team member indicator with the worker's previous log months of tenure at the parent firm to the explanatory variables included in Table 4. Spinoff team members with rare on-the-job skills that are transferable between firms should command higher retention rates. However, as the

coefficient in period $t+6$, which falls to 0.011. Results are qualitatively unchanged if we replace the six occupational categories with a full set of 354 occupation indicators.

Table 4: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, 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	.058	.087	.048	.039	.031	.033
	(.003)**	(.003)**	(.003)**	(.004)**	(.005)**	(.009)**
Some High School	.015	.024	.019	.006	.003	-.023
	(.003)**	(.005)**	(.005)**	(.005)	(.007)	(.017)
Some College	.007	.007	.005	-.006	-.008	.075
	(.004)	(.007)	(.007)	(.009)	(.017)	(.035)*
College Degree	-.001	.003	.009	-.020	-.015	-.007
	(.004)	(.006)	(.008)	(.010)*	(.012)	(.023)
Pot. lab. force exp.	-.004	.001	.007	.007	.004	.002
	(.001)**	(.002)	(.002)**	(.003)**	(.004)	(.006)
Sq. Pot. lab. force exp.	.0002	.00008	-.0003	-.0003	-.0002	.00003
	(.00006)**	(.0001)	(.0001)*	(.0002)	(.0002)	(.0004)
Cub. Pot. lab. force exp.	-4.00e-06	-3.56e-06	6.29e-06	4.11e-06	3.88e-06	-3.81e-06
	(1.48e-06)**	(2.56e-06)	(3.28e-06)	(4.16e-06)	(6.11e-06)	(1.00e-05)
Qrt. Pot. lab. force exp.	2.75e-08	3.13e-08	-5.24e-08	-2.27e-08	-3.84e-08	3.69e-08
	(1.23e-08)*	(2.05e-08)	(2.71e-08)	(3.53e-08)	(5.14e-08)	(8.96e-08)
Prev. Prof./Manag'l. Occ.	.015	.009	-.016	.002	-.010	.032
	(.005)**	(.007)	(.005)**	(.007)	(.009)	(.030)
Prev. Tech'l./Superv. Occ.	.012	.006	-.007	-.0009	-.002	.012
	(.004)**	(.007)	(.005)	(.007)	(.010)	(.029)
Prev. Unsk. Wh. Coll. Occ.	.004	-.002	-.010	.0004	.0006	.010
	(.003)	(.006)	(.005)	(.007)	(.010)	(.027)
Prev. Skld. Bl. Collar Occ.	.010	.003	-.009	-.003	-.002	-.019
	(.005)*	(.006)	(.005)	(.006)	(.008)	(.016)
Same *CNAE*	.003	.023	.013	.0005	.00009	-.030
	(.004)	(.004)**	(.004)**	(.007)	(.008)	(.013)*
Prev. Log months of tenure	.034	.040	.027	.019	.015	.022
	(.002)**	(.003)**	(.002)**	(.002)**	(.003)**	(.004)**
Female employee	.027	.042	.017	-.026	-.002	.015
	(.010)**	(.017)*	(.016)	(.022)	(.034)	(.052)
Obs.	1,082,238	583,620	263,726	115,589	46,244	16,381
R^2	.275	.255	.248	.273	.275	.292
Mean Dep. variable	.771	.684	.764	.795	.821	.806
Firm panels	68,340	45,109	23,897	12,386	5,404	1,935

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. Coefficients for interactions of female with all other worker characteristics not shown. Omitted category for occupation is unskilled blue collar. Occupation and tenure are for worker's last employment spell (lasting at least three months) before joining the spinoff. Tenure is measured as the log number of months worked at the previous employer. The indicator for same *CNAE* industry is defined for workers who had non-missing *CNAE* information 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 five, ** one percent.

Table 5: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, TRACKABLE WORKERS AND THE TEAM MEMBER-PARENT TENURE INTERACTION

Retention indicator	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Team member	.055	.108	.070	.040	.037	.040
	(.008)**	(.012)**	(.009)**	(.010)**	(.015)*	(.027)
Team mmb. × Prev. Log mo. of tenure	.001	-.008	-.008	-.0001	-.002	-.002
	(.003)	(.004)	(.003)*	(.003)	(.005)	(.008)
Obs.	1,082,238	583,620	263,726	115,589	46,244	16,381
R^2	.275	.255	.249	.273	.275	.292
Mean Dep. variable	.771	.684	.764	.795	.821	.806
Firm panels	68,340	45,109	23,897	12,386	5,404	1,935

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. Specifications control for same regressors as in Table 4 as well as female indicator and interactions. Tenure is for worker's last employment spell (lasting at least three months) before joining the spinoff and is measured as the log number of months worked at the previous employer. Clustered standard errors at the level of teams in parentheses: * significance at five, ** one percent.

results in Table 5 show, the coefficients on the interaction term are almost all negative and never statistically significant at the one-percent confidence level.

A different way to address the concern that the coefficients on the team indicator reflect scarce, relevant skills transferred from the parent to the spinoff firm is to try to control directly for the availability of these skills in the local labor market. We computed the number of workers in the birth year of the spinoff who are employed by firms in the same municipality and 4-digit *CNAE* industry as the spinoff's parent to proxy for the number of workers available in the local labor market with the same skills that are being acquired at the parent, and call this measure local labor market thickness. In Table 6 we show the regression results when we add the interaction of the log of this local labor market thickness measure with the team member indicator to the explanatory variables in Table 4.[23] If the retention hazard gap between team members and non-team workers is driven by the inability of the founding partners of the spinoff 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 indeed negative and statistically significant in the first and second years of employment, though not statistically significant thereafter. In Table 6 we also report adjusted team member coefficients; those are the implied coefficients on the team member indicator when

[23] We also added the interaction term to Table 3 with similar findings (results available upon request).

Table 6: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, TRACKABLE WORKERS AND LOCAL LABOR MARKET THICKNESS

Retention indicator	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Team member	.111	.111	.051	.034	.042	.069
	(.006)**	(.008)**	(.007)**	(.010)**	(.014)**	(.028)*
Tm. mmb. × Labor Mkt. Thickness	-.008	-.004	-.0006	.0006	-.002	-.005
	(.0007)**	(.001)**	(.001)	(.001)	(.002)	(.004)
Obs.	936,537	505,626	227,669	97,823	38,154	13,477
R^2	.273	.253	.248	.275	.289	.303
Mean Labor Mkt. Thickness	7.165	7.126	7.12	7.122	7.296	7.415
Mean Dep. variable	.776	.681	.763	.796	.823	.813
Adjusted Team member coefficient	.056	.083	.047	.039	.029	.030
Firm panels	55,853	37,178	19,711	10,246	4,500	1,621

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. Specifications control for same regressors as in Table 4 as well as female indicator and interactions. Labor market thickness is the number of workers in the birth year of the spinoff who are employed by firms in the same municipality and 4-digit *CNAE* industry as the spinoff's parent. Clustered standard errors at the level of teams in parentheses: * significance at five, ** one percent.

evaluated at the sample means of the log of our proxy for availability of workers similar to team members. These implied coefficients differ little from those in Table 4.

Another alternative hypothesis is that team members have innately higher ability, leading to their being retained more than non-team workers, with the retention gap closing as non-team workers with low innate ability are laid off. Team members with innately higher ability than non-team workers will have had higher wage residuals at their previous employers net of plant effects (their wage premia beyond observable worker characteristics and estimated employer effects). These Mincer log wage residuals were computed by Menezes-Filho, Muendler, and Ramey (2008) as part of their work with the RAIS data. In Table 7 we show the impact of adding these residuals to the right-hand sides of the retention hazard regressions in Table 4. The coefficients on the wage residuals are consistent with the view that innately higher ability influences retention of team members and non-team workers at spinoff firms. However, the coefficients are statistically significantly positive only initially (in periods $t+1$ and, at a lower significance level, $t+2$) but not thereafter. Moreover, the coefficients on the team member indicator are essentially unchanged compared to Table 4.

Table 7: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, TRACKABLE WORKERS AND THEIR WAGE RESIDUALS

Retention indicator OLS	$t+1$ (1)	$t+2$ (2)	$t+3$ (3)	$t+4$ (4)	$t+5$ (5)	$t+6$ (6)
Team member	.062	.091	.052	.045	.032	.043
	(.003)**	(.003)**	(.003)**	(.004)**	(.006)**	(.011)**
Prev. Log Dec. wage resid.	.015	.009	.007	.006	.006	.026
	(.003)**	(.004)*	(.005)	(.005)	(.006)	(.020)
Obs.	953,957	510,953	234,763	102,177	40,577	14,162
R^2	.283	.263	.258	.29	.293	.293
Mean Dep. variable	.768	.694	.77	.798	.825	.809
Firm panels	68,012	44,776	23,621	12,195	5,286	1,871

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. Specifications control for same regressors as in Table 4 as well as female indicator and interactions. Wage residual (wage premium beyond observable worker characteristics and estimated employer effects) is for a worker's last employment spell (lasting at least three months) before joining the spinoff. Clustered standard errors at the level of teams in parentheses: * significance at five, ** one percent.

Perhaps team members did not only have innately higher ability in general, but also had innately higher ability to do a task specific to the parent firm which they were recruited to do at the spinoff firm. In other words, workers with high wage residuals at parent firms were even more attractive to recruit and retain at spinoff firms than workers with high wage residuals at non-parent firms. To control for this possibility, in Table 8 we add the interaction of the wage residual with the team indicator to the right-hand side variables included in Table 7. The coefficients on this interaction are positive in all but one period and are statistically significant in periods $t+1$ and $t+4$, but do not decline with time. Most importantly, including this interaction does not qualitatively change the coefficients on the team member indicator itself.

Our model predicts that a spinoff's lower retention rates of non-team workers than team members will lead the wages at the spinoffs of the former to catch up to those of the latter, because the difference in retention rates is driven by separation from the spinoffs of non-team workers who are revealed to be poor fits. We check this prediction for the wage premium between team members and non-team workers among trackable workers in Table 9. We use the same right-hand side variables as in Table 4 but bring in as dependent variable the log wage instead of the retention hazard. Consistent with the predictions of our model, we find a monotonically declining wage premium

Table 8: WORKER-LEVEL RETENTION HAZARD GAP AT SPINOFF, TRACKABLE WORKERS AND THEIR WAGE RESIDUALS AMONG TEAM AND NON-TEAM MEMBERS

Retention indicator OLS	$t+1$ (1)	$t+2$ (2)	$t+3$ (3)	$t+4$ (4)	$t+5$ (5)	$t+6$ (6)
Team member	.062 (.003)**	.090 (.003)**	.051 (.003)**	.045 (.004)**	.033 (.006)**	.043 (.011)**
Prev. Log Dec. wage resid.	.006 (.002)**	.002 (.004)	-.0008 (.005)	-.005 (.007)	.013 (.010)	.008 (.017)
Team memb. × Prev. resid.	.015 (.004)**	.011 (.006)	.012 (.007)	.016 (.008)*	-.011 (.012)	.025 (.025)
Obs.	953,957	510,953	234,763	102,177	40,577	14,162
R^2	.283	.263	.258	.290	.293	.293
Mean Dep. variable	.768	.694	.77	.798	.825	.809
Firm panels	68,012	44,776	23,621	12,195	5,286	1,871

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. Specifications control for same regressors as in Table 4 as well as female indicator and interactions. Wage residual (wage premium beyond observable worker characteristics and estimated employer effects) is for a worker's last employment spell (lasting at least three months) before joining the spinoff. Clustered standard errors at the level of teams in parentheses: * significance at five, ** one percent.

for team members, with statistical significance fading as the spinoff firm ages.[24]

In summary, comparing retention hazard gaps and wage premia at spinoff firms between founding team members and non-team workers strongly supports the predictions of our social capital model. Conditional on firm effects, worker characteristics and market characteristics, 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 who have known match quality at the parent. The longer workers have

[24]Members of the founding team may have been able to "write their own job descriptions" and would therefore be willing to accept lower pay. We thus attribute little importance to the magnitudes, as opposed to the time trend, of the coefficients on the team member indicator. Findings are similar for the universe of workers as in Table 3 (results available upon request).

Table 9: WORKER-LEVEL WAGE PREMIUM FOR TEAM MEMBERS AT SPINOFF, TRACKABLE WORKERS

Log Wage Difference OLS	$t+1$ (1)	$t+2$ (2)	$t+3$ (3)	$t+4$ (4)	$t+5$ (5)	$t+6$ (6)
Team member	.050 (.003)**	.038 (.005)**	.034 (.006)**	.023 (.009)**	.021 (.015)	.029 (.016)
Obs.	812,930	382,302	192,483	88,292	36,730	13,151
R^2	.748	.766	.764	.75	.76	.733
Mean Dep. variable	5.707	5.745	5.743	5.701	5.82	5.791
Firm panels	65,510	41,637	22,186	11,552	5,021	1,825

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. Specifications control for same regressors as in Table 4 as well as interactions with female indicator. Clustered standard errors at the level of teams in parentheses: * significance at five, ** one percent.

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,

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

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.[25] 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.

Our benchmark general-equilibrium model omits the time required for the spinoff's founding partners to learn the match qualities of their close colleagues with their planned firm. In other words, we assume in the general-equilibrium version of our model that networks of size α arise instantaneously. This is not necessarily realistic, and in practice the probability that an employee belongs to the network of a potential entrepreneur should depend on his prior job history at parent firm i and in particular on his tenure τ. We thus allow for the possibility that a parent worker's

[25]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.

expected network size $\alpha_i(\tau)$ is a function of tenure and satisfies $\dot{\alpha}_i(\tau) > 0$. We expect $\dot{\alpha}_i(\tau)/\alpha_i(\tau)$ to be high initially given our fundamental assumption that potential entrepreneurs learn their close colleagues' match qualities with their planned firm faster than their employer learns the same workers' match qualities with the existing firm, but this fast learning also brings forward the time at which learning is complete and the rate of network formation may slow to a halt. The following proposition formally states the conditions under which this network formation process generates an inverted U in the probability that an employee departs the parent for the spinoff firm:

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. □

The condition of the proposition means that the network expansion rate exceeds the employer learning rate for employees with short tenure but that the rate of employer learning overtakes the network expansion rate in finite time. This occurs because employee entrepreneurs complete their learning about their colleagues quickly. 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 shape. 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 match 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. □

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.

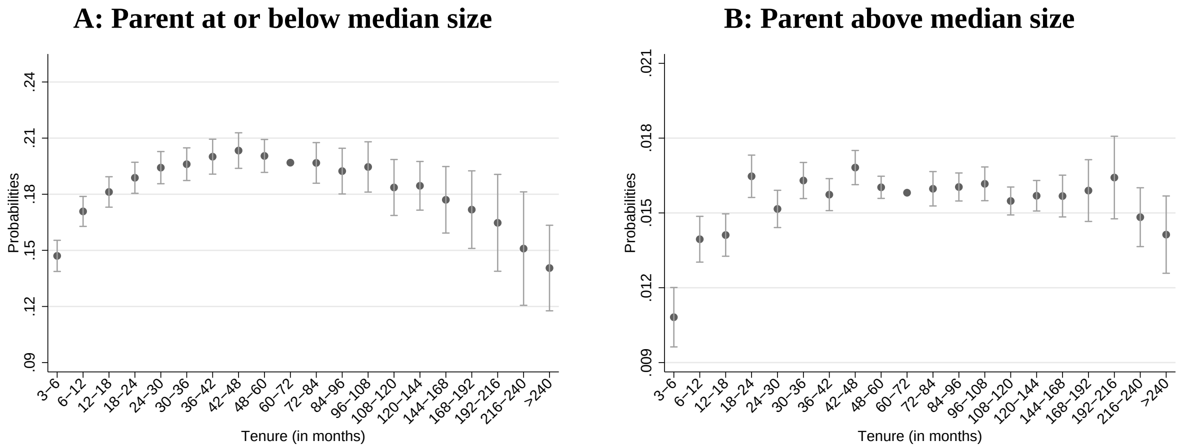
When comparing tenure at a parent firm between workers who join a spinoff and workers who remain at the parent, we must be careful to identify the correct choice set facing the entrepreneurs who are recruiting the workers. This consideration leads us to define the dependent variable for separation to spinoff as equal to one if a worker at a parent firm joins a spinoff born in the following year and zero otherwise.[26] 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 not applicable.[27]

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 convention 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.[28] 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. We restrict our sample of parents to those that survive until the end of our sample period in 2001, since workers may wish to separate from

[26]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.

[27]The assumption of our model that workers exit 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.

[28]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 13).



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 as well as current occupations and a full set of gender interactions. 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. 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 by Parent Size**

a dying parent regardless of match quality. In the regressions, we include a full set of worker controls (experience, education, occupation, gender, and gender interactions) and we 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. Tables C.1 and C.2 in Appendix C show the full set 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.

Figure 1 depicts the tenure bin results for departure hazard regressions among parent firms with size at or below median employment (62 employees) and parent firms with size above median employment. Small parent firms exhibit a marked inverse U shape, expected from Proposition 2, with a single peak in coefficient estimates at 42 to 48 months tenure. In contrast, large parent firms show a wide plateau for intermediate tenure levels. Note that the difference in scale between the left-hand and the right-hand graph arises because spinoffs are of similar sizes whereas parents differ in size. 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.[29] The feature that stands out across both graphs is the low departure hazards for short tenure levels.[30]

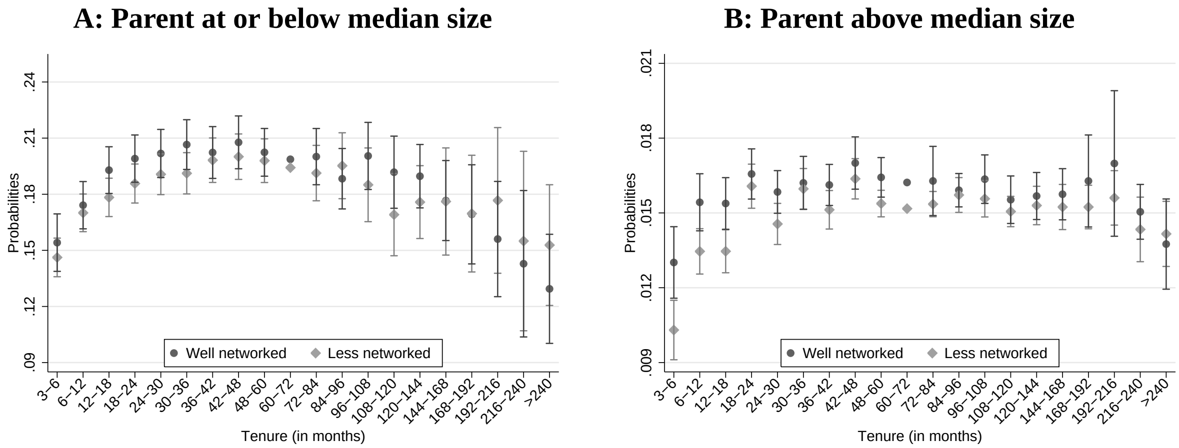
Our theoretical rationale for the increasing left arm of the inverted U is that workers with short tenure have smaller networks so that their prospective match quality with a spinoff is not yet known to many potential entrepreneurs. An alternative explanation might be that, in general, outside learning 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 3). 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. Note also that if spinoff entrepreneurs were recruiting parent workers for their firm-specific human capital, the probability of departure to spinoff would increase monotonically with tenure. Neither this alternative hypothesis nor the hypothesis that spinoff entrepreneurs recruit parent workers with generically high ability predicts that the probability of departure to spinoff eventually falls with 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).[31] The number of occupation changes at the parent is a proxy for 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 sev-

[29] We conjecture that an empirical explanation for the plateau could be found in internal labor markets at the parent firms, which are absent from our model and which we expect to be especially important at large parent firms.

[30] We relate the departure hazard to a worker's tenure, not firm age, and find that the departure hazard peak occurs at a considerably later tenure than the hump in separations from one-year old firms that we noted above. Moreover, we find no such peak when we examine transitions to non-spinoff employment or unemployment below. Our empirical findings in this section are thus unrelated to observations in Farber (1999); see also footnote 18.

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



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 as well as current occupations and a full set of gender interactions. 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. 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), interacted with the network indicator. Table C.1 in Appendix C shows the full set of coefficient estimates. Confidence intervals (95% significance) from clustered standard errors at the parent-year level by tenure-bin indicator, relative to omitted tenure bin.

Figure 2: **Departure Hazards of Parent Workers to Spinoffs by Parent Size and Network Extent**

eral 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.

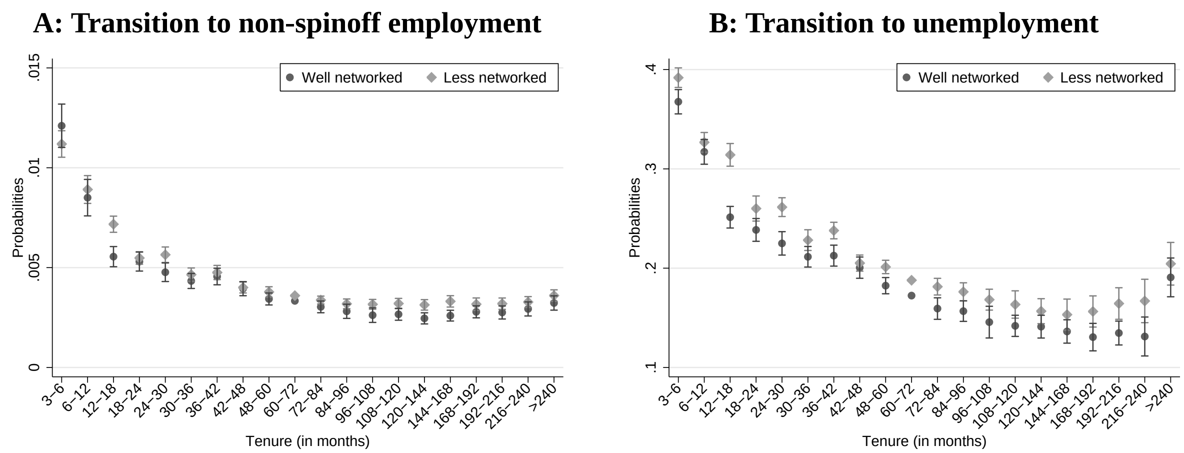
Figure 2 depicts the tenure bin results for both well networked employees with at least one occupation change (*well networked employees*) and employees with no occupation change at their current employer (*less networked employees*). In line with our social-capital explanation, well networked employees at large parents exhibit consistently higher hazards of departure to a spinoff at all tenure levels except greater than 240 months, though not always statistically significantly higher rates. Results for small parents are similar, but departure hazards for well-networked employees cease to be higher starting at 168-192 months of tenure. The sharpest results are for short-tenured employees at large parents: those with a background of at least one occupation change at the parent are more likely to depart to a spinoff than those 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. If occupation changes at the parent mainly reflected a worker's employer-specific expertise or career opportunities in the parent's internal labor market, and occupation changes did not have to do with the expansion of a worker's social network at the employer, then the departure hazard for a well networked worker should be strictly lower than that for a less networked worker because better internal labor-market opportunities would facilitate retentions especially at large parents. The opposite is the case: the departure hazard for workers with at least one occupation change is strictly higher than for workers with no occupation change, suggesting that occupation changes overwhelmingly reflect network expansions rather than internal labor-market opportunities.

We now turn to Proposition 3. The right-hand graph in Figure 3 shows the separation hazard of parent-firm workers who shift to unemployment, self employment or informal work (outside RAIS).[32] Consistent with Proposition 3, this separation hazard strictly declines with parent-firm tenure (until it levels off at 144-168 months), and similarly so for both well networked and less networked employees.[33] The left-hand graph in Figure 3 shows the separation hazard of parent-firm workers with a job-to-job transition to another formal-sector firm.[34] This separation hazard also strictly declines with parent-firm tenure until leveling off at 96-108 months. Revisiting our distinction between well networked multi-occupation employees and less networked single-occupation employees in the left-hand graph in Figure 3, the job-to-job transition hazard of well networked employees is generally 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

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

[33] The anomaly for tenure greater than 240 months is probably due to failure to record some retirements and deaths.

[34] 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 as well as current occupations and a full set of gender interactions. 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.2 in Appendix C shows the full set of coefficient estimates. Confidence intervals (95% significance) from clustered standard errors at the parent-year level by tenure-bin indicator, relative to omitted tenure bin.

Figure 3: **Separation Hazards of Parent Workers to Non-spinoff Employment and Unemployment**

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 for a worker's social network.

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 in that founding team workers were retained more frequently and received wage premia. The current results for parent-firm tenure offer additional evidence on the timing of learning consistent with the hypothesis that prospective spinoff entrepreneurs learn the match qualities of workers in their networks initially faster than employers learn the same workers' match qualities with their firms.

6 Quantifying the Aggregate Impact of Social Capital

In our model aggregate output is

$$\bar{X} = \bar{M}\bar{x} = \bar{M}\,\{\bar{q}\,\mu_H + (1-\bar{q})[p_0\,\mu_H + (1-p_0)\mu_L]\}\,, \tag{9}$$

where we used equation (1) to substitute for mean output per firm $\bar{x}$.[35] 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.[36] For all these employee spinoffs we assume that $q_i(0)$ equals $q(0)_{spin}$, the mean founding team member share in the spinoff workforce at entry in our data.[37] 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.

[35] 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.

[36] In an Online Supplement, 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.

[37] 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.

We can compute $q(t)_{\alpha=0}$ and $q(t)_{spin}$ using equation (5) and the respective initial conditions $q_i(0)_{\alpha=0} = 0$ and $q_i(0) = q(0)_{spin}$ for all i, to obtain

$$q(t)_{\alpha=0} = q^*(1 - \exp\{-(\delta + \theta\gamma + \phi p_0)t\}) \tag{10}$$

and

$$q(t)_{spin} = q^* + [q(0)_{spin} - q^*] \exp\{-(\delta + \theta\gamma + \phi p_0)t\}, \tag{11}$$

where q^* is given by equation (4). By equation (10), 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.

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 set γ to zero, and equations (10) and (11) simplify to

$$q(t)_{\alpha=0} = \frac{\phi p_0}{\delta + \phi p_0} \left(1 - \exp\{-(\delta + \phi p_0)t\}\right) \tag{12}$$

and

$$q(t)_{spin} = \frac{\phi p_0}{\delta + \phi p_0} + \left[q(0)_{spin} - \frac{\phi p_0}{\delta + \phi p_0}\right] \exp\{-(\delta + \phi p_0)t\}, \tag{13}$$

where we have substituted for q^* using equation (4). To use equations (12) and (13) 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 separate from firms only 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 in the Appendix 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 among Brazil's domestically-owned private-sector firms 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. Our estimates imply that 93 percent of the aggregate impact of social capital occurs in firms ages zero to four (as shown in Table D.3 in the Appendix), and during those first four years after entry 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

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 abilities and preferences of colleagues by no means exhaust the list of what employees learn inside a parent firm. Studies of select high-tech industries, for instance, demonstrate that spinoff firms learn their parents' technologies (e.g. Klepper and Sleeper 2005, Franco and Filson 2006). Muendler and Rauch (2011) document for the Brazilian economy that exporting spinoffs of exporting parents learn about their parents' export markets and export products. As detailed economy-wide data for spinoffs and their parents become increasingly available, we expect the study of employee spinoffs to provide valuable insight into the nature and economic consequences of learning inside firms and into the transmission of innovative knowledge throughout the economy.

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Appendix

A Individual Dynamics and Flow Value Restrictions

Value functions. Let P be an individual's value of being a spinoff partner, and let $V(p_0)$ and $V(1)$ be the values of employment with unknown and known match quality, respectively. We allow for a status outside formal work (informal work, self employment or unemployment) and call its value U. We can express the Bellman equations for an individual compactly as:

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

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

$$r\,U = b + \lambda[V(p_0) - U], \tag{A.2}$$

and

$$r\,P = a - \theta[P-U]. \tag{A.3}$$

To solve for the value functions in terms of fundamentals, we first restate equations (A.1) through (A.3) so that the value functions form a conventional linear system in the four unknowns $V(p_0)$, $V(1)$, U and P. For brevity, we 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 $c_4 \equiv (\delta+\theta)$. The restated equation system then becomes:

$$V(p_0) = \frac{w(p_0) + c_1 V(1) + c_2 P + c_3 U}{r + c_1 + c_2 + c_3}, \tag{A.4}$$

$$V(1) = \frac{\mu_H + c_2 P + c_4 U}{r + c_2 + c_4}, \tag{A.5}$$

$$U = \frac{b + \lambda V(p_0)}{r+\lambda}, \tag{A.6}$$

$$P = \frac{a + \theta U}{r+\theta}, \tag{A.7}$$

conditional on the value of the job finding rate λ. The job finding rate λ is an equilibrium outcome.

These relationships have intuitive interpretations. Consider equation (A.4), for instance:

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

The equation summarizes the vicissitudes that an individual in our model confronts. When an employee is of unknown match quality, 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 δ he is exogenously separated from his current employer, with probability θ his current employer exits, and with probability $\phi(1-p_0)$ the worker is revealed to have low match quality with his current employer.

Solving the equation system (A.4) through (A.7) for $V(p_0)$, $V(1)$, U and P yields

$$\begin{aligned} V(p_0) &= \frac{1}{rD}\Big\{(r+\lambda)(r+\theta)[(r+c_2+c_4)w(p_0) + c_1\mu_H] + (r+\lambda)c_2(r+c_1+c_2+c_4)\,a \\ &\quad +[r(c_1c_4 + (r+c_2+c_4)c_3) + (r(c_2+c_3) + (c_1+c_2+c_3)(c_2+c_4))\theta]\,b\Big\}, \end{aligned} \quad \text{(A.8)}$$

$$\begin{aligned} V(1) &= \frac{1}{rD}\Big\{[(r+\lambda)(r+\theta)c_1 + r(r+c_2+c_3)(r+\theta) + r(r+c_2+\theta)\lambda]\,\mu_H \\ &\quad +[(r+\theta)c_4 + \theta c_2][(r+c_1+c_2+c_3)b + \lambda w(p_0)] \\ &\qquad +[r(r+c_1+c_2+c_3) + (r+c_1+c_2+c_4)\lambda]c_2\,a\Big\}, \end{aligned} \quad \text{(A.9)}$$

$$\begin{aligned} U &= \frac{1}{rD}\Big\{(r+c_1+c_2+c_3)(r+c_2+c_4)(r+\theta)\,b \\ &\quad +\lambda(r+\theta)[(r+c_2+c_4)w(p_0) + c_1\mu_H] + (r+c_1+c_2+c_4)c_2\lambda\,a\Big\}, \end{aligned} \quad \text{(A.10)}$$

$$\begin{aligned} P &= \frac{1}{rD}\Big\{[r(r+c_1+c_2+c_3)(r+c_2+c_4) + (r+c_1+c_2+c_4)(r+c_2)\lambda]\,a \\ &\quad +(r+c_2+c_4)\theta[\lambda w(p_0) + (r+c_1+c_2+c_3)b] + c_1\lambda\theta\,\mu_H\Big\}, \end{aligned} \quad \text{(A.11)}$$

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).

Flow value restrictions. In equilibrium, the flow value a from implementing a spinoff idea and the flow value b of unemployment must be such that $P > V(1)$, $V(p_0) > U$ and $U \geq V(0)$. By equations (A.5) and (A.7), $P > V(1)$ if and only if $a > [(r+\theta)\mu + r\delta\,U]/(r+\delta+\theta)$.

By equation (A.6), $U < V(p_0)$ if and only if $b < rV(p_0)$. Similarly by (A.6), $U \geq V(0)$ 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 2.5). This value of b in turn determines the lower bound on a as stated above.

In terms of fundamentals, the lower bound a_L on the flow value of implementing a new firm satisfies $P = V(1)$. Setting (A.9) equal to (A.11) 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.8),

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

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 (A.1),

$$\begin{aligned} r\,V(0) &= \mu_L - (\delta+\theta)\,[V(0) - U] + \theta\gamma\,[P - V(0)] \\ &\quad +\theta(1-\gamma)\alpha p_0\,[V(1) - V(0)] \\ &= r\,\frac{\mu_L + c_2P + c_4U + c_5V(1)}{r + c_2 + c_4 + c_5}, \end{aligned} \tag{A.12}$$

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.12) simplifies to $V(0) = U = \{\mu_L + c_2P + c_5V(1)\}/\{(r + c_2 + c_5)\}$. Setting this expression equal to (A.10) 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 (8) 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 2.4 of the text, a firm i has a share $q_i(t) \in [0,1]$ of workers with known match quality 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 (7) from the text, where

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

by (6) 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 (4) 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. Accordingly, the mass of firms with known share q at birth (age zero) is $\rho(q,0)$. As t periods 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 is a contraction mapping, that is

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

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

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

It follows that

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

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 and Separation Hazards of Parent Workers

Table C.1 reports the probability estimates depicted in Figures 1 and 2. The coefficient estimates are from linear parent-year fixed effects regressions of departure indicators on the set of tenure-bin indicators, worker characteristics as in Table 3 as well as current occupations, and a full set of gender interactions. We retain in the sample only parent firms that have an employee spinoff in the subsequent year and that survive to 2001. In column 1 we further restrict the sample to parent firms with employment (size) at or below median employment; in column 2 we impose the converse restriction to parent firms with above median size. To preserve space, we show results from a single regression in columns 3 and 4, where we restrict the sample to parent firms with employment at or below median (as in column 1). The column pair 3-4 presents in column 3 coefficients on the interaction of tenure-bin dummies with an indicator for an employee being well networked and in column 4 coefficients on the plain tenure-bin dummies. We consider an employee with at least one occupation change at the parent as relatively well networked. The sum of the tenure-bin coefficients in columns 3 and 4 and the coefficient on the well-networked

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

	Fig. 1A	Fig. 1B	Fig. 2A		Fig. 2B	
Departure indicator			Well netw.	Less netw.	Well netw.	Less netw.
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Tenure 3-6 mo.	-.049	-.005	.003	-.048	.002	-.005
	(.004)**	(.0006)**	(.009)	(.005)**	(.0007)*	(.0006)**
Tenure 6-12 mo.	-.026	-.002	-.0004	-.024	.0009	-.002
	(.004)**	(.0004)**	(.008)	(.005)**	(.0006)	(.0005)**
Tenure 12-18 mo.	-.015	-.002	.010	-.016	.0009	-.002
	(.004)**	(.0004)**	(.008)	(.005)**	(.0005)	(.0004)**
Tenure 18-24 mo.	-.008	.0006	.009	-.008	-.0006	.0009
	(.004)	(.0004)	(.008)	(.005)	(.0005)	(.0004)*
Tenure 24-30 mo.	-.002	-.0006	.007	-.004	.0002	-.0006
	(.004)	(.0004)	(.008)	(.005)	(.0005)	(.0004)
Tenure 30-36 mo.	-.0006	.0005	.011	-.003	-.0008	.0008
	(.004)	(.0004)	(.009)	(.006)	(.0006)	(.0004)
Tenure 36-42 mo.	.003	-.0001	-.0004	.004	-.00005	-.00005
	(.005)	(.0003)	(.009)	(.006)	(.0005)	(.0004)
Tenure 42-48 mo.	.007	.001	.003	.006	-.0004	.001
	(.005)	(.0003)**	(.009)	(.006)	(.0005)	(.0004)**
Tenure 48-60 mo.	.004	.0002	9.76e-06	.004	1.71e-06	.0002
	(.004)	(.0002)	(.009)	(.006)	(.0004)	(.0003)
Tenure 72-84 mo.	-.0005	.0001	.004	-.003	-.0001	.0002
	(.005)	(.0003)	(.010)	(.007)	(.0006)	(.0003)
Tenure 84-96 mo.	-.005	.0002	-.011	.001	-.0009	.0005
	(.006)	(.0003)	(.012)	(.009)	(.0004)	(.0003)
Tenure 96-108 mo.	-.003	.0003	.011	-.009	-.0003	.0004
	(.007)	(.0003)	(.013)	(.010)	(.0004)	(.0004)
Tenure 108-120 mo.	-.014	-.0003	.018	-.025	-.0006	-.0001
	(.007)	(.0003)	(.014)	(.011)*	(.0004)	(.0003)
Tenure 120-144 mo.	-.012	-.0001	.009	-.018	-.0007	.0001
	(.006)	(.0003)	(.013)	(.010)	(.0005)	(.0004)
Tenure 144-168 mo.	-.020	-.0001	-.004	-.018	-.0005	.00006
	(.009)*	(.0004)	(.017)	(.014)	(.0004)	(.0005)
Tenure 168-192 mo.	-.027	.0001	-.005	-.025	-4.89e-06	.00006
	(.010)**	(.0006)	(.020)	(.016)	(.0007)	(.0004)
Tenure 192-216 mo.	-.031	.0006	-.025	-.018	.0003	.0004
	(.013)*	(.0008)	(.023)	(.019)	(.001)	(.0005)
Tenure 216-240 mo.	-.049	-.0009	-.017	-.039	-.0003	-.0008
	(.015)**	(.0005)	(.031)	(.024)	(.0006)	(.0006)
Tenure $\geq$ 240 mo.	-.056	-.002	-.028	-.041	-.001	-.001
	(.011)**	(.0007)*	(.021)	(.016)*	(.0005)**	(.0007)
Well-networked			.004		.001	
			(.007)		(.0004)*	

continued

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

OLS	Fig. 1A (1)	Fig. 1B (2)	Fig. 2A (3)-(4)	Fig. 2B (5)-(6)
continued				
Some High School	-.013	-.001	-.013	-.001
	(.002)**	(.0005)**	(.002)**	(.0005)**
Some College	-.037	-.003	-.037	-.003
	(.006)**	(.0005)**	(.006)**	(.0005)**
College Degree	-.065	-.005	-.065	-.005
	(.006)**	(.0005)**	(.006)**	(.0005)**
Pot. lab. force exp.	.001	-.001	.0005	-.002
	(.009)	(.0008)	(.009)	(.0008)
Sq. Pot. lab. force exp.	.006	.002	.006	.002
	(.006)	(.0005)**	(.006)	(.0005)**
Cub. Pot. lab. force exp.	-.003	-.0005	-.003	-.0005
	(.002)	(.0001)**	(.002)*	(.0001)**
Qrt. Pot. lab. force exp.	.0003	.00005	.0003	.00005
	(.0001)*	(1.00e-05)**	(.0001)*	(1.00e-05)**
Prof. or Manag'l. Occ.	-.013	.002	-.014	.002
	(.004)**	(.001)*	(.004)**	(.001)*
Tech'l. or Superv. Occ.	-.020	-.0006	-.020	-.0007
	(.004)**	(.0009)	(.004)**	(.0009)
Unskilled Wh. Collar Occ.	-.019	-.001	-.019	-.001
	(.004)**	(.0009)	(.004)**	(.0009)
Skilled Bl. Collar Occ.	.009	.0009	.009	.0009
	(.003)**	(.001)	(.003)**	(.001)
Female employee	-.041	-.001	-.041	-.001
	(.008)**	(.001)	(.008)**	(.001)
Obs.	445,002	2.84e+07	445,002	2.84e+07
R^2	.160	.263	.160	.263
Mean Dep. variable	.179	.015	.179	.015
Parent-year panels	21,541	21,656	21,541	21,656

Source: RAIS 1995-2001, parent firms that have employee spinoff in subsequent year and that survive to 2001.
Notes: The table shows one regression each in column 1, in column 2, in column pair 3-4, and in column pair 5-6. 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 parent-year level in parentheses: * significance at five, ** one percent.

indicator (final row of column 3 in first part of table) therefore represents the departure hazard to a spinoff for well networked employees by tenure bin, shown with the dark black dots in Figure 2. The coefficients in column 4 alone represent the departure hazard for the less networked employees by tenure bin, shown with the light grey dots in Figure 2. In column pair 5-6, we report results from a single regression restricting the sample to parent firms with employment above median (as in column 2). Column 5 shows the coefficient estimates for tenure bins interacted with the well networked indicator; and column 6 the coefficients on the plain tenure-bin dummies.

Table C.2 reports the probability estimates depicted in Figure 3. The coefficient estimates are from linear parent-year fixed effects regressions of separation indicators on the set of tenure bin indicators, worker characteristics as in Table 3 as well as current occupations, and a full set of gender interactions. We retain in the sample only parent firms that have an employee spinoff in the subsequent year and that survive to 2001. To preserve space, we show results from a single regression of an indicator for an employee's separation and subsequent employment at a non-spinoff in columns 1 and 2. We show results from a single regression of an indicator for an employee's separation with no subsequent formal employment in columns 3 and 4. The column pair 1-2 presents in column 1 coefficients on the interaction of tenure bins with an indicator for an employee being well networked and in column 2 coefficients on the plain tenure-bin dummies. The sum of the tenure-bin coefficients in columns 1 and 2 and the coefficient on the well-networked indicator (final row of column 1 in first part of table) therefore represents the separation hazard to a non-spinoff for well networked employees by tenure bin, shown with the dark black dots in Figure 3. The coefficients in column 2 alone represent the separation hazard for the less networked employees by tenure bin, shown with the light grey dots in Figure 3. Column pair 3-4 presents in column 3 coefficients on the interaction of tenure bins with an indicator for an employee being well networked and in column 4 coefficients on the plain tenure-bin dummies.

Table C.2: SEPARATION HAZARDS OF PARENT WORKERS TO NON-SPINOFF EMPLOYMENT AND UNEMPLOYMENT

	Fig. 3A		Fig. 3B	
Departure indicator	Well netw.	Less netw.	Well netw.	Less netw.
OLS	(1)	(2)	(3)	(4)
Tenure 3-6 mo.	.001	.008	-.009	.204
	(.0004)**	(.0003)**	(.006)	(.005)**
Tenure 6-12 mo.	-.0001	.005	.006	.139
	(.0004)	(.0003)**	(.006)	(.005)**
Tenure 12-18 mo.	-.001	.004	-.047	.126
	(.0002)**	(.0002)**	(.005)**	(.006)**
Tenure 18-24 mo.	.00008	.002	-.006	.072
	(.0002)	(.0002)**	(.006)	(.006)**
Tenure 24-30 mo.	-.0006	.002	-.021	.074
	(.0002)**	(.0002)**	(.004)**	(.005)**
Tenure 30-36 mo.	-.00006	.001	-.001	.040
	(.0002)	(.0002)**	(.006)	(.005)**
Tenure 36-42 mo.	.00006	.001	-.010	.050
	(.0002)	(.0002)**	(.005)	(.004)**
Tenure 42-48 mo.	.0002	.0004	.011	.017
	(.0002)	(.0001)**	(.005)*	(.004)**
Tenure 48-60 mo.	-.00009	.0002	-.003	.013
	(.0002)	(.0001)	(.004)	(.003)**
Tenure 72-84 mo.	-.00008	-.0002	-.007	-.006
	(.0002)	(.0001)*	(.005)	(.004)
Tenure 84-96 mo.	-.0001	-.0004	-.004	-.012
	(.0002)	(.0001)**	(.005)	(.005)*
Tenure 96-108 mo.	-.0003	-.0004	-.007	-.020
	(.0002)	(.0001)**	(.007)	(.005)**
Tenure 108-120 mo.	-.0003	-.0004	-.006	-.024
	(.0002)	(.0001)**	(.007)	(.007)**
Tenure 120-144 mo.	-.0004	-.0005	-.0001	-.031
	(.0002)*	(.0001)**	(.006)	(.006)**
Tenure 144-168 mo.	-.0005	-.0003	-.002	-.035
	(.0002)*	(.0001)*	(.007)	(.008)**
Tenure 168-192 mo.	-.0001	-.0004	-.010	-.031
	(.0002)	(.0002)**	(.008)	(.008)**
Tenure 192-216 mo.	-.0002	-.0004	-.014	-.023
	(.0002)	(.0001)**	(.008)	(.008)**
Tenure 216-240 mo.	-.00008	-.0003	-.020	-.021
	(.0002)	(.0001)*	(.013)	(.011)
Tenure $\geq$ 240 mo.	-.0001	3.28e-06	.002	.017
	(.0002)	(.0001)	(.011)	(.011)
Well-networked	-.0003		-.015	
	(.0001)*		(.004)**	

continued

Table C.2: SEPARATION HAZARDS OF PARENT WORKERS TO NON-SPINOFF EMPLOYMENT AND UNEMPLOYMENT, CONT'D

	Fig. 3A	Fig. 3B
OLS	(1)-(2)	(3)-(4)
continued		
Some High School	-.001	-.024
	(.0001)**	(.002)**
Some College	-.002	-.011
	(.0002)**	(.004)**
College Degree	-.002	-.015
	(.0002)**	(.003)**
Pot. lab. force exp.	.006	.117
	(.0004)**	(.011)**
Sq. Pot. lab. force exp.	-.003	-.064
	(.0003)**	(.006)**
Cub. Pot. lab. force exp.	.0005	.013
	(.00006)**	(.001)**
Qrt. Pot. lab. force exp.	-.00003	-.0009
	(4.53e-06)**	(.00009)**
Prof. or Manag'l. Occ.	-.0007	-.048
	(.0003)*	(.004)**
Tech'l. or Superv. Occ.	-.0004	-.050
	(.0003)	(.003)**
Unskilled Wh. Collar Occ.	-.0001	-.044
	(.0003)	(.004)**
Skilled Bl. Collar Occ.	.003	-.038
	(.0004)**	(.002)**
Female employee	-.003	-.033
	(.0004)**	(.007)**
Obs.	2.77e+07	2.77e+07
R^2	.023	.209
Mean Dep. variable	.005	.229
Parent-year panels	43,035	43,033

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 parent-year level in parentheses: * significance at five, ** one percent.

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, 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 we 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 year τ who are still employed in the next year $\tau{+}1$ depends on the share of workers that were of unknown match quality in 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 take the share of non-team workers of known match quality to be zero

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 five, ** one percent.

at the beginning of the second (instead of the first) year of operation of the employee spinoff, implying that $1 - q_{i0}(t+1) = 1$. Combining this insight 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 $q(0)_{\text{SPIN}} = 0.489$ (the observed initial share of workers of known match quality at spinoffs in our data) into equations (12) and (13) to compute $q(t)_{\alpha=0}$, $q(t)_{\text{SPIN}}$, and $q(t)_{\text{AGG}} = 0.29\, q(t)_{\text{SPIN}} + 0.71\, q(t)_{\alpha=0}$. Recall form the main text that 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 $q(t)_{\text{AGG}}$ to obtain our estimates of $\bar{q}_{\alpha=0}$ and $\bar{q}$, respectively.

In order to compute employment among Brazil's domestically-owned private-sector firms by firm age, we use the years in which these firms 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 $q(t)_{\text{SPIN}}$ 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.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	$q(t)_{\text{SPIN}}$	$q(t)_{\alpha=0}$	$q(t)_{\text{AGG}}$	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 $q(t)_{agg} = 0.29\,q(t)_{spin} + 0.71\,q(t)_{\alpha=0}$ based on equations (12) and (13) using δ and ϕp_0 from Table D.2 along with $q(0)_{spin} = 0.489$. Age and employment from RAIS 1986-2001.

Online Supplement to
Mobilizing Social Capital Through Employee Spinoffs

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E Alternative Quantification of the Aggregate Impact of Social Capital

In contrast with the quantification exercise in the main text, the supplementary exercise here maintains the model's assumptions that all firms have the same size and that all new firms are spinoffs, and uses coefficient estimates of departure hazards at parents in addition to coefficient estimates of retention hazards at spinoffs.

E.1 Theoretical lower bound on the aggregate impact of social capital

We start by restating aggregate output (9) from Section 6:

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

Aggregate output $\bar{X}$ increases with the economy-wide fraction of workers with known match quality $\bar{q}$. Social capital therefore contributes to aggregate output by raising the share of known workers at every entrant.

To quantify the importance of social capital for aggregate performance, it is helpful to find the economy-wide fraction of employees with known match quality $\bar{q}$ in the absence of social capital. We begin with the observation that $\alpha = 0$ implies $q_i(0) = 0$ for all firms i. If there is no networking at the parent, then spinoffs have to start with a completely unknown workforce. Subsequently, the fraction of known workers $q_{i,\alpha=0}(t)$ is determined entirely by the age of the firm. From equation (7), we have

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

When it helps clarity, we abbreviate the rate of convergence with

$$\eta \equiv \delta + \theta\gamma + \phi p_0.$$

In the absence of social capital, the share of known workers at birth is zero so that the initial deviation from steady state is $-q^*$. Subsequently, the share of known workers strictly increases and becomes arbitrarily close to q^* (a vanishing difference between $q_{i,\alpha=0}(t)$ and q^* as firm age increases arbitrarily).

The Poisson process of birth and exit of firms at rate θ yields an exponential steady state distribution of firm age with parameter θ. Concretely, the steady state fraction of firms with age less than t is $G(t) = 1 - \exp\{-\theta t\}$. Changing variable from t to q, we obtain the steady state fraction of firms with a share of known workers less than q, $F_{\alpha=0}(q)$. We use equation (E.1) to solve for t as a function of q. Rearranging and taking natural logarithms of both sides, we have

$$\ln(q^* - q) = \ln(q^*) - \eta t \quad \text{or} \quad t = [\ln(q^*) - \ln(q^* - q)]/\eta.$$

Making the change of variable then yields

$$\begin{aligned} G[t(q)] &= 1 - \exp\{-(\theta/\eta)\ln(q^*)\}\ \exp\{(\theta/\eta)\ln(q^* - q)\} \\ &= 1 - (q^* - q)^{\theta/\eta}/(q^*)^{\theta/\eta}. \end{aligned}$$

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

$$F_{\alpha=0}(q) = 1 - \left(\frac{q^* - q}{q^*}\right)^{\theta/\eta}. \tag{E.2}$$

Using the density associated with this distribution function, we integrate over q between 0 and q^* and obtain a remarkably simple expression for the economy-wide average q in the absence of social capital:[38]

$$\bar{q}_{\alpha=0} = \frac{1}{1 + \theta/\eta}\, q^* = \frac{\phi p_0}{\delta + \theta(1+\gamma) + \phi p_0}. \tag{E.3}$$

As the rate of growth $\eta = (\delta + \theta\gamma + \phi p_0)$ of each firm's $q_i(t)$ to the long-term known-worker share

[38] The density is $f_{\alpha=0}(q) = (\theta/\eta)[1/(q^* - q)][1 - F_{\alpha=0}(q)]$ so that the indeterminate integral over q becomes $\int q\, \mathrm{d}F_{\alpha=0}(q) = -[\theta q + \eta q^*][1 - F_{\alpha=0}(q)]/[\delta + \theta(1+\gamma) + \phi p_0]$.

increases, or as the rate of firm exit and entry θ becomes small, $\bar{q}_{\alpha=0}$ approaches q^* under (4). The reason is that the value of q for all but the youngest firms will be near q^*, or nearly all firms are old. On the other hand, as the growth rate of $q_i(t)$ to its long-term value becomes small, or as the rate of firm entry and exit becomes large, $\bar{q}_{\alpha=0}$ approaches zero. The reason now is that the value of q for all but the oldest firms will be near $q_i(0) = 0$, or nearly all firms are young.

The smaller is $\bar{q}_{\alpha=0}$ in the absence of social capital, the greater is the scope for social capital to increase aggregate output. From equation (E.3) we therefore see that the potential effect of social capital on aggregate output increases with the rate of spinoff creation θ and decreases with the rate of employer learning ϕ.

We cannot compute $\bar{q}_{\alpha>0}$ in the presence of social capital because we lack a closed-form solution for the distribution of q in the population of firms when there is social capital (see Theorem 1 and its proof in Appendix B). Therefore we cannot compute the difference in the share of known workers with and without social capital $\Delta\bar{q} = \bar{q}_{\alpha>0} - \bar{q}_{\alpha=0}$. However, we can derive a formula that establishes a *lower bound* for the increase in $\bar{q}$ attributable to social capital.

Consider a benchmark parent with a share of workers with known match quality $q_p(t_{i0}) = q^*$ and the case where a spinoff from the parent starts with $q_i(0) < q^*$. From equation (6) we know that the share of workers with known match quality at startup is

$$q_i(0) = [1 - q_p(t_{i0})]\psi \quad \text{for} \quad \psi \equiv (1-\gamma)\alpha p_0 < 1. \tag{E.4}$$

It follows that $(1 - q^*)\psi < q^*$ for the benchmark parent with $q_p(t_{i0}) = q^*$. Our evidence in the next subsection will show that the case $(1 - q^*)\psi < q^*$ is the empirically applicable one. For this case we can state the following lemma.

Lemma 3. *Suppose the condition $(1 - q^*)\psi < q^*$ is satisfied. Then the bounds on the steady-state distribution of q in the presence of social capital are $(1 - q^*)\psi$ and q^*.*

Proof. We will call the steady-state support $[(1-q^*)\psi, q^*]$ the *absorbing interval*. Consider a firm in the absorbing interval, with $q_i(t) \in [(1 - q^*)\psi, q^*]$. By the firm dynamics under equation B.1, a firm in the absorbing interval cannot age to a $q > q^*$. The firm cannot be parent to a spinoff with $q_i(0) < (1 - q^*)\psi$ because no parent has a known match-quality share larger than q^* in the absorbing interval, so that the lowest possible q for a spinoff to start with is $q_i(0) = [1 - q^*]\psi$. Moreover, the largest possible q for a spinoff from a parent in the absorbing interval is $q_i(0) =$

$[1-(1-q^*)\psi]\psi$. It it straightforward to show that $[1-(1-q^*)\psi]\psi < q^*$ by the condition of the lemma.[39] The interval $[(1-q^*)\psi, q^*]$ is therefore an *absorbing interval*: no firm that enters this interval can exit it other than by death, nor can its spinoffs start outside the interval.

Next, consider a firm with $q_i(t) \in (q^*, 1]$. This firm will age to q^* from above or exit. All spinoffs of this firm will start with $q_i(0) \in [0, (1-q^*)\psi)$. Finally, consider a firm with $q_i(t) \in [0, (1-q^*)\psi)$. This firm will evolve into the absorbing interval or exit. The maximal share of workers with known match quality at a spinoff from this firm is ψ because the least informed parent at $q_p(t_{i0}) = 0$ spawns a spinoff with $q_i(0) = (1-0)\psi = \psi$. For a sufficiently small social network α, the best spinoff starts inside the absorbing interval with $\psi \leq q^*$, where $\psi \leq q^*$ is equivalent to $\alpha \leq \phi/[\eta(1-\gamma)]$ by the definitions of ψ and q^* in (E.4) and (4). We have thus shown for sufficiently small social network size $\alpha \leq \phi/[\eta(1-\gamma)]$ that, beginning from a point in time when there is a positive mass of firms in each of the intervals $[0, (1-q^*)\psi)$, $[(1-q^*)\psi, q^*]$, and $(q^*, 1]$, there will be a continual shift of the mass of firms into the absorbing interval $[(1-q^*)\psi, q^*]$, or exit, and no shift of the mass of firms out of this interval. Since the mass of firms is constant, it follows that as age t grows arbitrarily large the mass of firms outside the absorbing interval vanishes.

The proof for a large social network size $\alpha > \phi/[\eta(1-\gamma)]$ (so that $\psi > q^*$) is a little more involved. Note that spinoffs from a parent in the interval $q_i(t) \in [0, 1-q^*/\psi)$ start with $q_i(0) \in (q^*, \psi]$ for large network size. To establish that the steady-state support $[(1-q^*)\psi, q^*]$ is also the absorbing interval for large network size, we need to show that spinoffs stop entering into the adjacent interval $q_i(0) \in (q^*, \psi]$ as parent age t grows arbitrarily large. It is useful to state the following sequence of equivalent inequalities, which all follow from the single condition of the lemma $(1-q^*)\psi < q^*$:

$$(1-q^*)\psi < q^* \;\Leftrightarrow\; 1 - \frac{q^*}{\psi} < (1-q^*)\psi < \frac{\psi}{1+\psi} < q^*.$$

Figure E.1 depicts the respective points. Note that parents in the adjacent interval $(q^*, \psi]$ spawn spinoffs that start in the interval $q_i(0) \in [(1-\psi)\psi, (1-q^*)\psi)$. As a consequence, no new firm starts below the lower threshold $(1-\psi)\psi = \psi \sum_{t=0}^{1}(-\psi)^t$, and incumbent firms evolve into the absorbing interval or exit, so that the mass of firms in the left-most interval $[0, (1-\psi)\psi)$ vanishes.

[39] For a spinoff to start with $q_i(0) = q^*$, the parent must have $q_i(t) = 1 - q^*/\psi$. Note that another parent with $q_i(t) = (1-q^*)\psi$ must have a higher share of known workers because $(1-q^*)\psi > 1 - q^*/\psi$ is equivalent to the condition of the lemma $(1-q^*)\psi < q^*$. Therefore a spinoff from a parent with $(1-q^*)\psi$, which starts with $q_i(0) = [1-(1-q^*)\psi]\psi$, must start strictly below q^*. Figure E.1 depicts the three points $\{1-q^*/\psi, (1-q^*)\psi, q^*\}$.

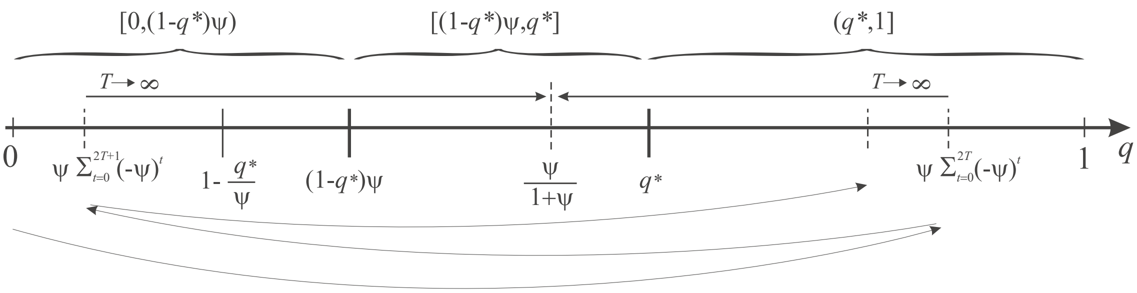

Figure E.1: Illustration of Lemma 3

In turn, parents at $(1-\psi)\psi$ or above spawn spinoffs at or below $\{1-(1-\psi)\psi)\}\psi < \psi$. As a consequence, no new firm starts above the upper threshold $\{1-(1-\psi)\psi\}\psi = \psi\sum_{t=0}^{2}(-\psi)^t$ anymore, and incumbent firms evolve towards the absorbing interval or exit, so that the mass of firms in the upper part of the adjacent interval $[\{1-(1-\psi)\psi)\}\psi, \psi]$ vanishes. Thus the upper threshold above which no startup enters is $\psi\sum_{t=0}^{2T}(-\psi)^t$, which converges to $\psi/(1+\psi)$ from above as $2T = 0, 2, 4, 6, 8, \ldots$ grows arbitrarily large. The lower threshold below which no startup enters is $\psi\sum_{t=0}^{2T+1}(-\psi)^t$, which converges to $\psi/(1+\psi)$ from below as $2T+1 = 1, 3, 5, 7, 9, \ldots$ grows arbitrarily large. (Parents at $\psi/(1+\psi)$ spawn spinoffs with $\psi/(1+\psi)$, while parents with $q_i(t) < \psi/(1+\psi)$ spawn spinoffs with $q_i(0) > \psi/(1+\psi)$ and vice versa.) Since the upper threshold ultimately crosses q^* (because $\psi/(1+\psi) < q^*$), no new firm starts outside the absorbing interval anymore. The mass of firms is constant, so it follows that as T grows arbitrarily large the mass of firms outside the absorbing interval vanishes also for large social network size. □

Lemma 3 states that, in the presence of social capital, all new firms in steady state are founded with a share of workers with known match quality at least as large as $(1-q^*)\psi$. In the absence of social capital, new firms start with a known match-quality share of zero. By the empirically confirmed condition of the lemma, all new firms start with a known match-quality share lower than the known match-quality share in very old firms, which is intuitively plausible. In the following Proposition, we use Lemma 3 to establish a lower bound on the impact of spinoff-mobilized social capital on $\bar{q}$.

Proposition 4. *Suppose the condition $(1-q^*)\psi < q^*$ is satisfied. Then the lower bound on the* *increase in $\bar{q}$ attributable to spinoff-mobilized social capital equals*

$$\Delta\bar{q}_{\min} = \frac{\theta(1-q^*)\psi}{\delta+\theta(1+\gamma)+\phi p_0}. \tag{E.5}$$

Proof. This expression is the difference between $\bar{q}_{\alpha=0}$ from (E.3) and the same integral with the lower limit $(1-q^*)\psi$ instead of zero. Since the limits of integration are the bounds on the true steady-state distribution of q, the latter integral computes what the value of $\bar{q}_{\alpha>0}$ would be if all new firms were born with $q_i(0) = (1-q^*)\psi$. Since $(1-q^*)\psi$ is actually the lower bound for $q_i(0)$ for all firms, and $q_i(0)$ evolves towards q^* at the same rate for all i, the distribution used to compute $\bar{q}_{q_i(0)=(1-q^*)\psi}$ is first-order stochastically dominated by the true distribution of q in the population of firms. It follows that $\bar{q}_{q_i(0)=(1-q^*)\psi} < \bar{q}$. □

The expression $\Delta\bar{q}_{\min}$ increases with network size α since $\psi = (1-\gamma)\alpha p_0$ increases with α. The expression also increases with θ, the rate of entry and exit of new firms, because social capital operates by increasing the share of workers with known match quality at new firms. Finally, the expression decreases with ϕ, the rate of employer learning, since employer learning is a substitute for the employee learning embodied in social capital (note that q^* increases with ϕ).

To quantify the lower bound impact of social capital on $\bar{q}$ in (E.5), we use estimates from the following subsection.

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

The entry rate of spinoffs in our model is θ. In this calibration exercise, we maintain our model's assumption that all new firms are spinoffs. In line with this assumption, we use the rate at which new firms enter as our measure of θ. We compute this rate for each year in our sample and divide the number of new firms entering in that year by the number of existing firms (see Table E.1). For our final estimate of θ, we average these rates over all seven sample years, which yields $\theta = 0.0816$. Though this is an unweighted average, it is virtually identical to the employment-weighted average (0.0814).

The separation hazard for team members of any tenure with a spinoff firm is constant at $\delta + \theta\gamma$. If we set γ to zero as for our main quantification exercise (Section 6 and Appendix D), the separation hazard for team members equals δ. We can estimate the separation hazard for team

Table E.1: ESTIMATES OF THE ENTRY RATE θ

	1995	1996	1997	1998	1999	2000	2001	Average
Number of Firms	564,129	573,953	618,630	645,704	668,765	700,636	754,893	646,673
Incumbent	523,575	533,028	564,294	597,168	617,750	647,972	702,067	597,979
New	40,554	40,925	54,336	48,536	51,015	52,664	52,826	48,694
Entry Rate θ	0.0775	0.0768	0.0963	0.0813	0.0826	0.0813	0.0752	0.0816

Source: RAIS 1995-2001, employee spinoff firms.
Note: Definition of employee spinoff (quarter-workforce criterion) as described in MRT.

members separately for each time period, using our regression results. Our preferred specification is that of Table 3 in the main text. For each period, the sum of the coefficients on the team indicator β and the retention hazard for non-team workers yields an estimate of $1-\delta$, the retention hazard for team members. As our estimate of the retention hazard for non-team workers we use the sample mean of the retention indicator for non-team workers in the regression sample of Table 3. Table E.2 reports β, the retention hazard for non-team workers, and 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 we calibrate our model.

Calibration of the employer learning rate ϕ, the unconditional probability p_0 that a random match will be high quality, and the social network size α 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.

We start by restating how we infer the learning rate ϕ, similar to our derivations for the main calibration exercise in Appendix D. 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 $\beta = [1-q_{i0}(\tau)][\phi(1{-}p_0){+}\theta\alpha p_0]$. This difference is equal to the coefficients on the team indicator β in our retention hazard regressions in Table 3. 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:

$$\beta(\tau{+}1) = [1-q_{i0}(\tau)](\phi{-}\phi p_0 + \theta\alpha p_0). \tag{E.6}$$

For $\tau = t+1$, this equation simplifies to

$$\beta(t{+}2) = \phi{-}\phi p_0 + \theta\alpha p_0 \tag{E.7}$$

Table E.2: ALTERNATIVE PARAMETER ESTIMATES

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	Average
Retention hazard gap β	0.0732	0.1058	0.0601	0.0432	0.0364	0.0207	
Non-team worker retention hazard rate	0.7169	0.6081	0.7171	0.7641	0.7929	0.7817	0.7301
Team-member separation rate δ	0.2099	0.2861	0.2228	0.1928	0.1707	0.1976	0.2133
Unknown match qual. sh. $1-q_{i0}$	1	0.5680	0.4079	0.3437	0.1954		
Employer learning rate ϕ	0.5117	0.3159	0.1743	0.4417			0.3609
Unconditional match qual. p_0	0.8442	0.7477	0.5427	0.8195			0.7385
Social network size α	0.3794	0.4283	0.5902	0.3908			0.4472

Notes: The retention hazard gap β is the coefficient estimate for the team members indicator in the retention regression in Table 3 (first row). The non-team worker retention hazard is the predicted retention rate from all regressors of Table 3, 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 (E.9) with firm age. The employer learning rate ϕ follows from (E.10), the unconditional probability of high match quality p_0 from (E.7), and social network size α from (E.11).

because, as stated for the main calibration exercise in the text, we take the share of non-team workers of known match quality to be zero at the beginning of a spinoff's second (instead of the first) year of operation, so $1-q_{i0}(t+1)=1$.

Equation (E.6) can also be rewritten in terms of growth factors so that the constants ϕ and p_0 drop out:

$$\frac{\beta(\tau+2)}{\beta(\tau+1)} = \frac{1-q_{i0}(\tau+1)}{1-q_{i0}(\tau)}. \tag{E.8}$$

Using $1-q_{i0}(t+1)=1$ (from our convention that the share of non-team workers of known match quality is zero at the beginning of the second year) and combining it with the above equation allows us to infer

$$1-q_{i0}(\tau+1) = [1-q_{i0}(\tau)]\beta(\tau+2)/\beta(\tau+1) \tag{E.9}$$

recursively for $\tau+1 = t+2, \ldots, t+5$. Table E.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

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

after setting γ 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

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

after some manipulation. Using equations (E.6) and (E.8) in that last expression allows us to solve for ϕ in terms of the retention hazard gap coefficients, the share of non-team workers with unknown match quality $[1 - q_{i0}(\tau)]$ and $\theta\alpha p_0$:

$$\phi = [1-q_{i0}(\tau)]\beta(t+2) - \frac{[1-q_{i0}(\tau+1)]-[1-q_{i0}(\tau)]}{[1-q_{i0}(\tau)]} - \theta\alpha p_0. \tag{E.10}$$

Our last step is to solve for αp_0. To do this, note that Figures 1 and 2 in the main text show a peak at 42-48 months (3.5-4 years) of tenure for the departure hazards of parent workers to spinoffs. It is reasonable to assume that social networks are fully formed by then, so we can use the departure hazard to spinoffs for workers with 42-48 months of tenure to help calibrate αp_0. As our measure of departure hazard, we average the probability estimate at 42-48 months of tenure (shown in Figure 3) for parents below or at the median size with the probability estimate for parents above median size, yielding an overall departure hazard estimate of 0.1101.[40] Setting γ to zero, this departure hazard equals

$$0.1101 = \alpha p_0[1 - q_{i0}(t+4)]. \tag{E.11}$$

Using the unknown match-quality share $[1 - q_{i0}(t+4)]$ among non-team workers only, instead of a firm's overall unknown match quality share $[1 - q_i(t+4)]$, presupposes that all workers at the parent with three-and-a-half to four years of tenure are non-team workers. Also note that the correct formula for the departure hazard is multiplied by θ. That is because the true departure hazard would be computed over all existing firms, not just parents. Since we condition on firms that actually have spinoffs, and the larger parents have spinoffs every year, a conservative approach is to assume that the parent has a spinoff with probability one in every year.

Equation (E.11) produces an estimate of αp_0 equal to 0.3203. Plugging this value into equation (E.10) yields estimates of ϕ for $\tau = t+1, ..., t+4$. Regardless of τ, however, the coefficient

[40] Probability estimates are obtained from parent-year fixed effects regression of the departure hazard to spinoff on the set of tenure bin indicators, conditional on worker characteristics as in Table 3 as well as current occupations, the log monthly wage and a full set of gender interactions. The probability estimate for workers with 42-48 months of tenure is the coefficient on a dummy for this tenure bin plus the predicted value from remaining regressors (including the constant for the omitted tenure bin coefficient of 60 to 72 months). The probability estimate is 0.2034 for firms below median size, and 0.0168 for firms above median size. Median size is 62 employees.

$\beta(t+2)$ is the same in all calculations of ϕ. Once we have ϕ, we can use equation (E.7) to solve for $p_0 = 1 - [\beta(t+2) - \theta\alpha p_0]/\phi$ and equation (E.11) to solve for $\alpha = 0.1101/\{p_0[1 - q_{i0}(t+4)]\}$. Table E.2 reports the results.

The above estimates allow us to compute the lower bound on the aggregate impact of social capital under the maintained assumptions of the model. We first verify that the condition of Lemma 3 holds empirically. By the preceding estimates, $\psi = \alpha p_0 = 0.3203$, and q^* can be computed using the estimates from Table E.2 in (4) to obtain $q^* = 0.5555$. We then have $0.1424 = (1 - q^*)\psi < q^* = 0.5555$.

We can therefore use the estimates in the last column of Table E.2 to compute the lower bound on the relative counterfactual drop in $\bar{q}$ (the economy-wide fraction of employees with known match quality) that would occur if spinoff-mobilized social capital were absent. Similar to the computations in the main text, our measure is the ratio

$$\frac{\Delta \bar{q}_{\min}}{\bar{q}_{\alpha=0}}.$$

Using our estimates from Table E.2 in the formulas (E.5) and (E.3), we obtain $\Delta \bar{q}_{\min} = 0.0207$ and $\bar{q}_{\alpha=0} = 0.4747$, yielding a counterfactual 4.4 percent increase in $\bar{q}$ attributable to spinoff-mobilized social capital.

F Sectoral and Occupational Characteristics of Spinoffs

To further characterize properties of spinoffs, we tabulate frequencies of employee spinoffs by sector and tabulate frequencies of occupations within spinoffs.

Table F.1 shows the distribution of both new and existing firms by sector and knowledge intensity. Following MRT and the definitions in the paper, we restrict the sample of new firms to those with at least five employees at foundation so as to separate employee spinoffs. Compared to existing firms, new firms and especially employee spinoffs occur slightly less frequently in Brazil's non-high-tech sector by the OECD (2001) classification. In contrast, new firms and especially spinoffs are founded more frequently than existing firms in the high-tech manufacturing sector and in knowledge-intensive services. Looking at individual industries, employee spinoffs are founded considerably less frequently than existing firms in commerce and the hospitality industry (hotels and restaurants). In contrast, spinoffs occur particularly frequently compared to the distribution

Table F.1: DISTRIBUTION OF NEW FIRMS BY SECTOR AND KNOWLEDGE INTENSITY

OECD (2001) classification, CNAE 1-digit sector	New Firms[a]			Existing Firms[b]
	Spinoffs	Divest.	Unrelated	
Non-high-tech sectors	81.7%	82.4%	82.8%	84.4%
High-tech manufacturing[c]	2.4%	2.6%	1.5%	1.8%
Knowledge-intensive services[d]	15.3%	14.5%	14.9%	13.3%
Agriculture and fishery	1.6%	1.7%	1.3%	1.6%
Mining, food processing and textiles	8.1%	8.2%	8.1%	5.9%
Manufacture of wood, metal products, chemicals	8.7%	8.2%	7.0%	6.5%
Manufacture of machinery and equipment	2.9%	3.0%	2.3%	2.1%
Utilities and construction	7.2%	6.1%	8.5%	3.3%
Commerce, repair services, hotels and restaurants	40.3%	50.0%	46.2%	50.5%
Transport, telecommunication, finance, insurance	4.9%	4.6%	3.4%	4.1%
Real estate activities and business services	17.8%	10.8%	13.0%	14.5%
Education, health, social and public services	4.2%	3.8%	4.4%	5.3%
Other social or personal services	3.7%	2.9%	4.8%	5.8%
Unknown	.6%	.5%	.8%	.4%

[a]New firms with at least five employees.

[b]Includes all formal sector firms reported in RAIS, including those with *natureza juridica* coded as Public administration, State-owned limited liability company, State-owned closed corporation, Corporation with some state control, Cooperative, Consortium, Business group, or Branch of foreign company.

[c]Includes High-tech and Medium-high-tech manufacturing.

[d]Includes Telecommunication, Finance and insurance, Business services (excluding real estate activities), Education and health services.

Source: RAIS 1995-2001.
Notes: High-tech and knowledge-intensity classification according to OECD (2001) based on *CNAE* 4-digit industry. Entry size is the total of founding employees with employment at any time during the new firm's first year.

Table F.2: OCCUPATION SHARES AT SPINOFF, TEAM VS. NON-TEAM

	Employees in	
	Team (1)	Nonteam (2)
Prof. or Manag'l. Occ.	.139 (.0004)***	.098 (.0003)***
Tech'l. or Superv. Occ.	.174 (.0004)***	.166 (.0004)***
Unskilled Wh. Collar Occ.	.160 (.0004)***	.173 (.0004)***
Skilled Bl. Collar Occ.	.407 (.0005)***	.396 (.0005)***
Unskilled Bl. Collar Occ.	.120 (.0003)***	.168 (.0004)***
Observations	954,326	819,331

Source: RAIS 1995-2001, workers at employee spinoff firms in the founding year.
Notes: Definition of employee spinoff (quarter-workforce criterion) as described in MRT. Occupations at present employer. (Table 2 reports previous occupations at last employer.) Standard errors in parentheses.

of existing firms in real estate and business services, construction, and the manufacture of wood, metal products, and chemicals.

Table F.2 reports the frequencies of occupations within non-team workers and team workers at spinoffs in their founding years. Within white-collar occupations, the relatively more skill intensive professional/managerial and technical/supervisory occupations are more frequent among the team members (who previously worked for the same parent firm), whereas the unskilled white-collar occupations are less frequent than among the non-team workers (who did not work for the parent firm). Similarly within blue-collar occupations, the more skill intensive occupations are also more frequent among the team members than among non-team members. As Table 2 documents, team members also used to work in more skill intensive occupations at their previous employer than did (trackable) non-team members.