Workers' skills and the post-entry dynamics of new spin-offs*

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Abstract

Despite the increasing interest in firm growth and survival over the last decades, research on how the dynamics of new firms – and particularly spin-offs – is related to the characteristics of their initial workforce is still scarce. This paper uses a large longitudinal matched employer-employee dataset to study how spin-offs' post-entry employment growth, worker flows and survival are associated to their initial human capital endowments. We focus on three measures of human capital at entry: the average skill level of workers, their skill dispersion and the share of co-workers in the workforce. In order to measure workers' skills, we use a multidimensional skill index that takes into account both observed and unobserved characteristics of the worker. Our results show that firms employing a more skilled workforce at the start-up and a higher share of co-workers face lower exit rates. In contrast, skill dispersion at entry increases the risk of exit and significantly reduces post-entry employment growth, by increasing spin-offs' separation rates. Finally, spin-offs entering with a more significant share of co-workers in the initial workforce survive longer and seem to suffer less significant labor adjustments over their lifecycle.

Keywords: Entrepreneurship, Spin-offs, Firm Growth, Firm Survival, Human Capital, Worker Turnover
JEL Codes: J24, J63, L25, L26, M13

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1 Introduction

Research on firm growth and survival has been accumulating at a remarkable pace over the last decades, being one of the central topics in the entrepreneurship field (Coad, 2009; Leitch et al., 2010; McKelvie and Wiklund, 2010). Understanding how entrepreneurs survive in the market, and how their firms can grow and create sustainable jobs constitutes a well-documented and still timely debate among scholars, policy makers and business-owners, especially following one of the worst financial and economic crisis in decades, marked by the closure of many firms and massive layoffs (OECD, 2010; 2013a).

What has been left aside by most of this already vast literature is how the dynamics of new firms (in terms of survival, growth and labor adjustments over firms' lifecycle) are related to the characteristics – specifically the skills – of the workers these firms employ at entry. Although a large empirical literature suggests that workers' outcomes are associated with firms' characteristics (see, for instance, the literature on firm size-wage effects), very little is known about the converse relationship. This neglect of the literature is indeed surprising, given that any level of employment growth can be achieved by different combinations of hires and separations (Burgess et al., 2000), so we may expect that a strong association between firm growth, labor reallocation and initial workers' skills actually exists. Moreover, labor is probably the most heterogeneous of all inputs in production functions (Lazear and Oyer, 2007), so matching the right firms to the right workers is expected to create economic value of a magnitude that few other economic processes can, and hence to have important effects on firm survival.

The lack of proper longitudinal data matching firms and workers partially explains why the potentially significant link between firms' initial choice of worker mix and subsequent firms' outcomes was overlooked for long time (Haltiwanger et al., 1999, 2007; Hamermesh, 2008; Iranzo et al., 2008). In this line, this study aims at understanding how the growth and survival patterns of new firms are related to the characteristics of the workers they employ at the time of entry, using a rich matched employer-employee dataset for Portugal. We focus on a significant group of new start-up firms that are established every year – spin-offs launched by individuals who have recently left their job either due to the identification of a business opportunity (pulled spin-offs), or by necessity (pushed spin-offs) – and where hiring strategies and, thus, initial workforce characteristics, may be particularly relevant to explain their post-entry performance (see Song et al., 2003; Franco and Filson, 2006; Agarwal et al., 2011; Muendler et al., 2012; Andersson and Klepper, 2013).

The paper focuses on three particular aspects of spin-offs' initial workforce: the average skill level of the first employees, their skill dispersion, and the share of co-workers at entry.[1] Regarding skill measurement, we follow the strategy proposed by Portela (2001) and use a multi-dimensional index of workers' skills, which allows considering both observable and unobservable characteristics of the workers employed by spin-offs at the time of entry. This approach constitutes a novel contribution to the existing literature, as previous studies have mostly focused on very particular and observable characteristics of workers to measure their skills (e.g., Ilmakunnas et al., 2004; Haltiwanger et al., 1999, 2007; Ilmakunnas and Ilmakunnas, 2011; Lopez-Garcia and Puente, 2012; Koch et al., 2013).

The main contributions of this study are twofold. First, we follow 50,656 new spin-offs established during the period 1992-2007 and analyze how the aforementioned initial human capital endowments are related to spin-offs' growth rates, worker flows (hires and separations) and survival. Second, we test whether, accounting for a set of firm, industry and entrepreneurs characteristics, any significant differences remain between pushed and pulled spin-offs in terms of employment growth and survival. To the best of our knowledge, this is the first study analyzing how those firm-level outcomes are related to the characteristics of the workforce hired at the time of entry, focusing particularly on pushed and pulled spin-offs.

The remaining sections of the paper are organized as follows. Section 2 briefly reviews the main literature relating firms' outcomes with workers' skills, and discusses the human capital measures used in this study. Section 3 describes the data and the methodological details about the computation of the skill index. Section 4 presents some descriptive and comparative statistics on the employment dynamics and workers' skills for pushed and pulled spin-offs. Section 5 presents the empirical models and discusses the results. Section 6 concludes.

2 Firm-level outcomes and workforce characteristics

2.1 Previous literature and theoretical background

There is an increasing integration and interdependence of the fields of industrial and labor economics (Haltiwanger et al., 1999, 2007; Ilmakunnas et al., 2004; Mamede, 2008). New firm performance – in terms of growth and survival – is a topic where this connection is particularly clear. On the one hand, the interesting issue from the point of view of industrial economics is how we can explain firms' post-entry performance with the fact that the "quality" and the "mix" of workers they start with is different. On the other hand, from

[1] Co-workers are defined as those workers hired by the new spin-off at the start-up and who were previously employed in the parent firm where the spin-off's founder comes from.

the labor economics perspective, an imperative issue is how new firms might contribute to job creation, destruction and labor turnover over their lifecycle.

Labor reallocation has been documented to be particularly significant among new and young firms (e.g., Abowd et al., 1999a; Burgess et al., 2000; Davis et al., 2009; Haltiwanger et al., 2013). Imperfect information – either in the form of information asymmetry (Gibbons and Katz, 1991) or matching quality (Jovanovic, 1979, 1984) – is argued to play a key role in this process of workers' reallocation at the firm-level (Abowd et al., 1999a). Actually, as firms get themselves sorted out and survive in the market, they probably identify their best workers, or the particular "skill mix" they require, and gradually move towards their desired team (Geroski and Mazzucato, 2002; Haltiwanger et al., 2007). As a result, firm-level employment growth rates and exit decisions may reflect adjustments in firms' (and entrepreneurs') perceptions about their own ability and efficiency.

While much attention has been paid to the role of the human capital of the founder(s) (Rauch et al., 2005; Koch et al., 2013), the relationship between workers' human capital and firm performance has been relatively neglected. However, under the resource-based theory of competitive advantage (e.g., Barney, 2001), human capital – understood as the most universally valuable and imperfectly imitable resource – is believed to explain why some firms outperform others (Crook et al., 2011). In times of increasing internationalization and a continuous acceleration of technological development, human capital endowments are recognized to be important preconditions to obtain information about markets and technologies, to remain connected and reactive in the market, to maintain and strengthen the competitiveness, and to give satisfactory signals to both clients and competitors (Rauch et al., 2005; Koch et al., 2013). Furthermore, initial human capital endowments may play an even more important and strategic role in newborn firms, which typically have less well-developed resources (e.g., immature internal structures, lack of reputation, and insufficient access to networks) and face higher exit rates, and which, therefore, need to find specific strategies to compete successfully with incumbents and to be able to grow.

The existing studies evaluating the role of human capital have mostly focused on firm productivity and workers' observed characteristics. So far, empirical evidence for U.S. (Haltiwanger et al., 1999, 2007), Finland (Ilmakunnas et al., 2004) and Spain (Lopez-Garcia and Puente, 2012) confirmed that firms employing more educated workforces are more productive on average (see also Crook et al. (2011) for a survey of results on other firm-level outcomes and for other countries). Similar results were obtained for Italy by Iranzo et al. (2008), who alternatively used the person fixed effects from an estimated wage equation (with both worker and firm fixed effects) as a measure of workers' skills. Studies analyzing how workers' skills may influence firm employment and survival dynamics are however much more scarce. The recent study by Koch et al. (2013), for Germany, has attempted to fill this gap, showing that employing a larger share of highly educated workers in the year of start-up has a significant positive impact on new firms' post-entry growth.

This paper, thus, tries to understand how the growth and survival of new spin-offs is related to their human capital endowments at the time of entry. Besides, we pay further attention to the heterogeneous nature of spin-offs, as not all spin-offs arise from the identification of an opportunity by some employee(s), or from some strategic action of incumbent firms. Several spin-offs also emerge from necessity (e.g., to escape from unemployment or unstable job conditions), though only more recent studies started recognizing their importance (e.g. Buenstorf, 2009; Bruneel et al., 2013; Dick et al., 2013).

Although most of those studies have been suggesting that pulled spin-offs outperform their pushed counterparts by surviving longer, recent evidence has also found that, after controlling for a number of start-up conditions where these firms differ, pushed and pulled spin-offs' exit rates are not significantly different (Rocha et al., 2013). Evidence on the role of initial workforce skills on pushed and pulled spin-offs' employment dynamics and survival is still limited, so this paper tries to contribute to this emerging debate, by evaluating whether the type of spin-off becomes imprinted in these firms' DNA, possibly leading to enduring post-entry performance differences, even after controlling for the characteristics of workers, business-owners, firms and industries.

2.2 Human capital measures

In this paper, we use three variables to measure the human capital endowments of pushed and pulled spin-offs at the moment of start-up: the average skill level of the initial workforce, the workers' skill dispersion at entry, and the share of co-workers hired at the start-up.

While the literature generally agrees on a positive association between workers' average skills and firm performance (usually measured by firm productivity), the effects potentially arising from skill dispersion are not so clear-cut. On the one hand, diversity (in tangible and intangible resources) within firms is often considered to be positively related to performance (Lazear, 1999; Ilmakunnas and Ilmakunnas, 2011; Østergaard et al., 2011; Koch et al., 2013), as a diversified workforce may raise the firm's ability to react and adapt to external shocks, improve the firm's problem-solving routines, besides providing access to a broader set of resources and increased information about global markets, potentially making the firm more creative, innovative and open to new ideas.

On the other hand, workers' heterogeneity also increases the need for interaction and communication, as it may lead to conflicts, distrust, rivalry, dissatisfaction, poor cooperation among workers and increased transaction costs (Parrotta et al., 2012). Moreover, according to the O-ring theory of production function (Kremer, 1993), workers are normally sorted out according to their skills, so people of similar skills are expected to work together and firms tend to specialize either in low-skill or in high-skill workers.

Empirical results on this relationship are still scanty and ambiguous. For Finland, Ilmakunnas and Ilmakunnas (2011) found that age (education) diversity is positively (negatively) related to firm productivity, while Østergaard et al. (2011) and Parrotta et al. (2012) obtained the reverse relationship, both for Denmark.[2] Martins (2008) and Iranzo et al. (2008), instead, measured workers' skills through the person-specific effect obtained from a wage equation. The former concluded, for Portugal, that an increase in workers' heterogeneity is associated with a decrease in firm productivity, whereas the latter, using Italian data and distinguishing between production and nonproduction workers, found positive (negative) effects from within-occupation (between-occupation) skill diversity. Hence, we contribute to this literature by analyzing not only the role of workers' average skills, but also the effect of workers' skill dispersion at the moment of entry – measured by the standard deviation of the average skill index of the initial workforce.

Finally, regarding the presence of co-workers in the initial workforce, the literature suggests that this may constitute a possible source of competitive advantage for the firm. By working as a possible channel through which routines, procedures, knowledge and various forms of capital may be transferred from the parent firm (Audretsch and Keilbach, 2005; Franco and Filson, 2006), co-workers may actually be a firm-specific resource – therefore, difficult to imitate.

Nonetheless, a stronger presence of co-workers at entry may also moderate the post-entry growth of new spin-offs. On the one hand, the choice of the initial workforce is documented to have long-term, persistent, effects, not only due to the informal ties developed between the first employees and firms' founders (Koch et al., 2013), but also because firing is costly and time consuming (Messina and Vallanti, 2007), potentially restricting subsequent labor adjustments at the firm-level.

On the other hand, information asymmetries may be mitigated (and/or match quality may be improved) in firms where co-workers have a more relative importance at the start-up, thus reducing the need for great labor reallocation after entry – which may be translated into lower hiring and separation rates –, though potentially reducing firm exit risks. Given these mixed arguments and the lack of empirical evidence on this relationship, we also consider the effect of this measure of human capital in our analysis.

[2] The study by Østergaard et al. (2011) however focuses on the relationship between employee diversity and firm innovation.

3 Data and Methodological Issues

3.1 Data and identification of spin-offs

Our data come from Quadros de Pessoal (hereafter, QP), a large longitudinal linked employer-employee dataset obtained from the Portuguese Ministry of Employment. QP covers all firms operating in the Portuguese private sector and employing at least one wage earner. Every year, each of those firms is legally obliged to fill in a survey and to report information on each of its establishments and workers. Available information at the firm-level includes employment, sales, industry, ownership, location, among others. At the individual-level, QP reports information about each worker's age, education, gender, qualifications, wages, occupational category, tenure, number of hours worked and type of contract. All firms, establishments and workers are identified with a unique identification number, so that they can be followed and matched over time. For these reasons, QP provides very rich and reliable micro data, allowing the identification of entries and exits of firms, BOs and workers, besides making possible to track individuals' trajectories and transitions across firms, industries, locations, occupational categories, among others.

Raw QP files are available for the period 1986-2009.[3] Entries of new firms are identified by the first time (year) a firm is recorded in QP files. New spin-offs are identified as a particular group of start-up firms entering in t, whose founder(s) was/were in paid employment in $t-1$ or $t-2$ and who left the previous employer. For spin-offs founded by two or more BOs in each year t, we have required that all of them were employed in the same incumbent firm, and that all of them have left their previous employer immediately before (in $t-1$ or $t-2$) engaging in the creation of the spin-off.

Pushed spin-offs were then distinguished from pulled spin-offs according to the potential triggering event driving the individuals' decision to start a business. Spin-offs founded in t by an individual (or a set of individuals) coming from an incumbent firm that either closed or suffered a significant downsizing in $t-1$ or $t-2$ were classified as "pushed spin-offs".[4] In this case, the creation of their own business may actually be a response of some employees to an adverse shock in the parent firm, being possibly closer to necessity-based spin-offs. The remaining cases were classified as "pulled spin-offs", which may either include "incumbent-backed spin-offs" – i.e., corporate spin-offs that are the result of opportunities exploited by an incumbent firm – or cases closer to "opportunity spin-offs" – that is, businesses initiated by one or more employees that identify an opportunity and who decide to explore

[3] There is a gap for the particular years of 1990 and 2001 in the worker-level files, for which no information was gathered at the individual-level.

[4] Following OECD (2013b), a significant downsizing corresponds to a reduction in firm size larger or equal to 30% of the workforce, with a minimum number of separations equal to five.

it independently of their employer (see Buenstorf, 2009; Bruneel et al., 2013). We are not able to distinguish these two last cases in our data.

We have followed the employment growth and survival patterns of 50,656 spin-offs identified in QP data – 16,001 pushed and 34,655 pulled –, which entered during the period 1992-2007 (excluding 2001).[5,6] The analysis stops at 2007, the last year for which we can identify the exit of firms. Firm exit is identified by the moment when a firm ceases to answer the survey. Following previous studies that also use QP dataset (e.g., Mata and Portugal, 2002; Geroski et al., 2010), we have required an absence of the firm from the files larger or equal to two years in order to identify its definite exit.[7] Data for 2008 and 2009 were only used to check the presence or absence of firms in QP files.

3.2 Measuring workers' skills

Previous studies have already recognized that finding the right measure of skills is quite controversial (Iranzo et al., 2008). As already discussed, most of the existing studies constructed human capital proxies based on *observed* dimensions as workers' educational attainment, age, earnings or gender (e.g., Haltiwanger et al., 1999, 2007; Ilmakunnas et al., 2004; Ilmakunnas and Ilmakunnas, 2011; Koch et al., 2013). However, since the seminal contribution of Abowd et al. (1999b), it is well known that worker heterogeneity can exceed considerably the differences across individuals in terms of the observable variables mentioned above, which only imperfectly reflect *unobserved* differences as innate ability, informal skills or education quality (see also Iranzo et al, 2008; Martins, 2008).

As a result, we provide a methodological contribution to the existing literature using the multi-dimensional skill index developed by Portela (2001) to measure workers' skills. This index synthesizes different observable and unobservable dimensions of the productivity of workers – in this case, schooling, experience and unobservable permanent heterogeneity. Accordingly, we started by computing the skill index of each worker i in each year t as follows:

[5] Due to the missing data at the worker-level for 2001, we are not able to identify the BO(s) of firms entering in this year. As our classification of spin-offs into "pushed" or "pulled" requires detailed information about the origin of BO(s) founding the firm, entries occurring in 2001 had to be excluded.

[6] About 97% of the 50,656 spin-offs under analysis are either limited liability companies (*Sociedades por Quotas*) or one-person business (*Empresário em Nome Individual*). From the 16,001 pushed spin-offs identified, 10,161 were established after the parent firm closure and the remaining 5,840 emerged after a significant downsizing of the parent firm.

[7] We define exit as firm closure. Despite the comprehensiveness of QP dataset, it does not allow the distinction between different modes of exit. Regarding the exits due to mergers or acquisitions (M&A), prior studies (e.g., Geroski et al., 2010) have documented that less than 1% of the total number of liquidations in Portugal has been due to M&A, thus suggesting that our inability to identify mergers in QP is not likely to affect our results.

$$S_{it} = mschool * a_{\text{school}} * a_{\text{experience}} * a_{\text{unobserved ability}}$$

where:

- $mschool$ is the average schooling years in the economy in each year;
- a_{school} is a correction factor taking into account the actual position of the individual, in each year, in the schooling distribution, being computed as follows:

$$a_{\text{school}} = 0.5 + \frac{\exp((school_i - mschool)/sschool)}{1+\exp((school_i - mschool)/sschool)},$$

where $school_i$ stands for the schooling level (in years) of worker i and $sschool$ represents the standard deviation of schooling in the population;

- $a_{\text{experience}}$ is a correction factor for worker's experience, conditional on their schooling level, calculated as follows:

$$a_{\text{experience}} = 0.5 + \frac{\exp((age_i - mage|school_i)/(sage|school_i))}{1+\exp((age_i - mage|school_i)/(sage|school_i))},$$

where age_i represents the age (in years) of worker i, $mage|school_i$ is the average age of the population within schooling level $school_i$ and $sage|school_i$ is its standard deviation;

- $a_{\text{unobserved ability}}$ is a correction factor for worker's unobserved ability, conditional of their schooling level and experience, calculated as follows:

$$a_{\text{unobserved ability}} = 0.5 + \frac{\exp((FE_i - mFE|school_i, age_i)/(sFE|school_i, age_i))}{1+\exp((FE_i - mFE|school_i, age_i)/(sFE|school_i, age_i))},$$

where FE_i denotes the worker-specific effect, $mFE|school_i, age_i$ is the average of those worker fixed effects for individuals with the same schooling and age, and $sFE|school_i, age_i$ is the standard deviation of those effects.

In order to estimate the worker fixed effect, a two high-dimensional fixed-effects wage equation was estimated using the procedure described in Guimarães and Portugal (2010). The dependent variable was defined as the natural log of real hourly earnings.[8] This wage equation controls for individual's age (and its square), tenure (and its square), education

[8] Hourly earnings correspond to the ratio between total regular payroll (base wages and regular benefits) and the total number of normal hours worked in the reference period. Earnings were deflated using the Consumer Price Index. Outliers (i.e., the 1% with highest and lowest real hourly log earnings in each year) were removed from the estimations.

dummies, qualification dummies, time dummies and, following Abowd et al. (1999b), both worker and firm unobserved (permanent) heterogeneity.

The computation of the skill index for each worker i in each year t has then allowed the construction of firm-level measures of workers' skills. In particular, for each firm, at the moment of entry, we have computed the average value and the standard deviation of their workers' skills, two of the key variables to be included in our empirical analysis – *Average Workers' Skills* and *Skill Dispersion*. With this last variable we aim at measuring the workforce inequality within the firm, in terms of skills, in the year of start-up. The higher (lower) the *Skill Dispersion*, the more heterogeneous (homogeneous) will be the initial workforce in terms of skills.[9]

4 Employment dynamics and workers' skills in pushed and pulled spin-offs

4.1 Employment growth, job and worker flows over firms' lifecycle

Figure 1 depicts the evolution of pushed and pulled spin-offs' growth rates over the years. On average, pulled spin-offs tend to present higher growth rates (3.9% against 1.3% for pushed spin-offs), though the growth rates of both groups of firms seem to converge as they age.[10] Growth rates tend to be higher during firms' infancy, becoming lower and even negative as firms become older, suggesting that most of the jobs are created at younger ages, while at more mature stages firms tend to stagnate or reduce their average size. The data actually reveal that average growth rates become negative relatively early, in part because many spin-offs close down and exit few years after start-up. About 28% of all spin-offs exit during the first three years of activity and only 64% survive at least five years. Conditional on survival, the average growth is found to be positive – though also decreasing – throughout the first eight to nine years of firm activity. The variability of growth rates also decreases over firms' lifecycle (see the right-hand side plot of Figure 1).

[9] It is possible to have some missing values in particular years at the firm-level, especially for firms employing only one worker, if some of the components of the skill index have missing data. Nevertheless, this does not seem to affect our results, given that the overall conclusions remain unchanged even when we exclude those firms from the dataset.

[10] However, we should notice that pushed spin-offs enter at a slightly larger scale – the mean and median start-up size of pushed spin-offs in our data is 5 and 3 employees, respectively; the respective values for pulled spin-offs are 4 and 2 employees.

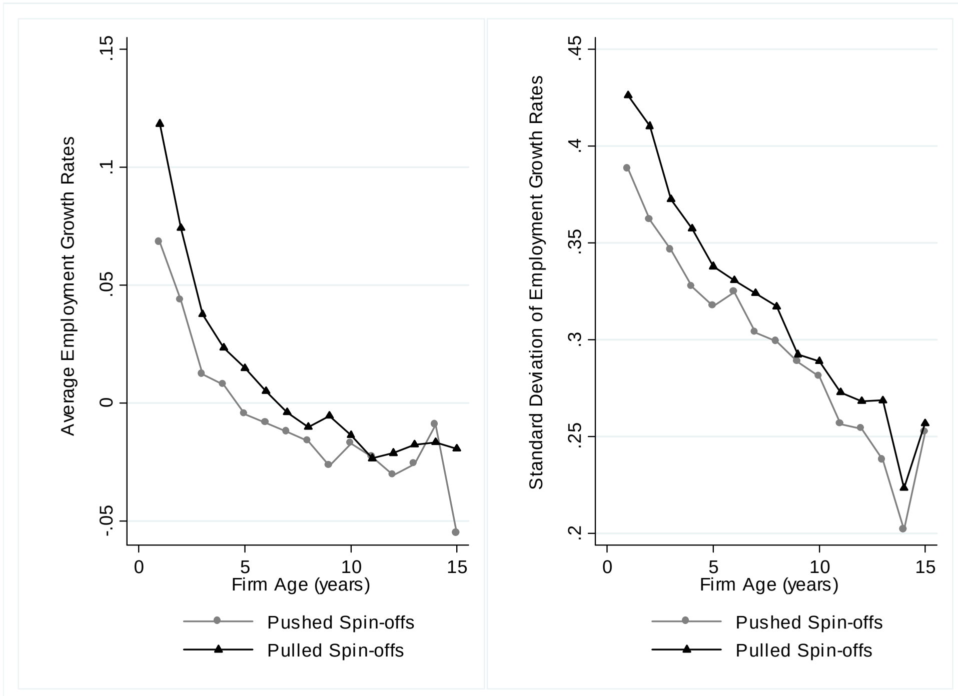

Fig. 1. Employment growth rates over firms' lifecycle, by spin-off type (average and std. dev. of growth rates)

Figure 2 plots the job reallocation rate, the worker flow rate and the churning rate over time, comparing, over again, pushed with pulled spin-offs. We follow Davis and Haltiwanger (1990, 1992) and Davis et al. (1996, 2006) in order to compute these rates.

Job flows refer to the annual change in employment at the firm-level: $JF_{it} = E_{it} - E_{it-1}$. Accordingly, job creation (destruction) is a positive (negative) job flow. We define job reallocation at the firm-level as the absolute value of job flows ($JR = |JF|$). Total worker flows are defined as the sum of hires and separations, $WF_{it} = H_{it} + S_{it}$, so that job flows are also defined as $JF_{it} = H_{it} - S_{it} = E_{it} - E_{it-1}$. Worker flows can thus be rewritten as $WF_{it} = JR_{it} + CF_{it}$, where the second term denotes "Churning Flows" – the number of worker flows over and above those necessary to achieve the firm's desired employment change. Hence, worker flows comprise two main components: firms simultaneously hiring and firing (i.e., firms churning workers) and workers quitting and being replaced (i.e., workers churning firms). The corresponding rates are the levels divided by the current average size of the firm ($(E_{it} + E_{it-1})/2$).

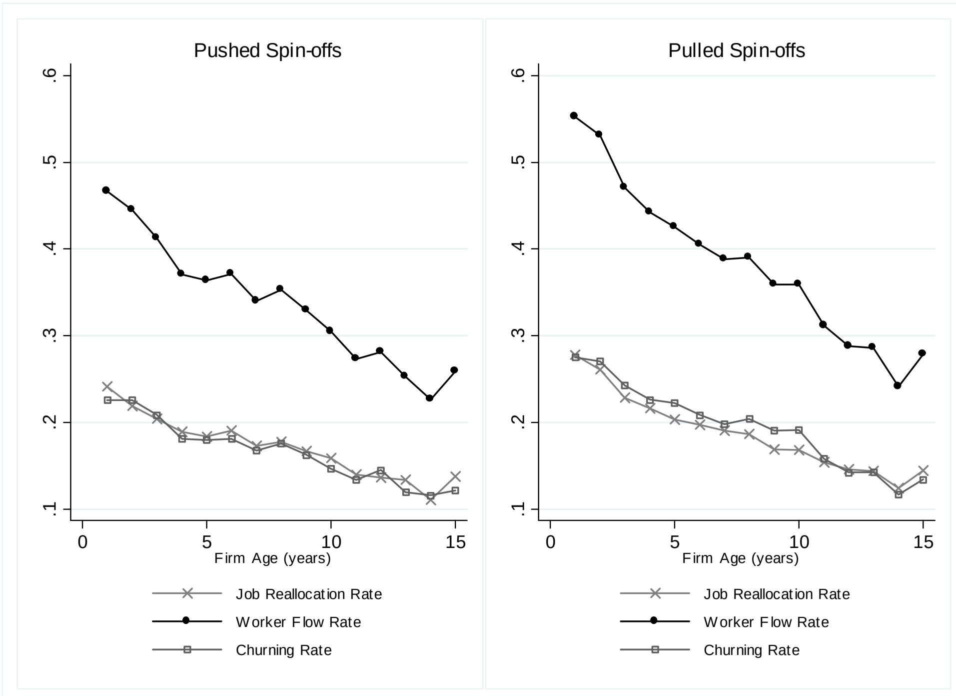

Fig. 2. Job and worker flows over firms' lifecycle

We observe, first of all, a clear pattern for the worker flow rate to decline with firm age, deriving from a decline in both job reallocation and churning rates. The data further show that worker turnover was higher in pulled than in pushed spin-offs. Overall, these patterns confirm that new spin-offs suffer a significant reallocation of workers over their lifecycle, especially during the first years of activity. As firms evolve over time, they probably have to decide and adjust the optimal mix of workers to employ. The fact that worker flows decline over firms' lifecycle may actually sign the already discussed behavioral and learning process at the firm-level – as firms age and learn about themselves and the market, they possibly identify their best workers/matches and/or the particular skill mix they require, and gradually adjust their workforce towards their desired team.

Table 1 additionally shows that while job destruction rates and separation rates were more similar among pulled and pushed spin-offs, the former exhibited higher job creation rates, as well as higher hiring rates. In summary, the data suggest that pulled spin-offs make more significant adjustments in their workforce after entry, while pushed spin-offs probably enter with a more stable worker mix, in part due to a stronger presence of co-workers and the potential knowledge advantages that may arise from them. In the year of start-up, about

19% of the initial workforce of pushed spin-offs is composed by co-workers, while in pulled spin-offs only 5% of the employees come from the parent firm.

In alternative, pushed spin-offs may have greater difficulties in adjusting their workforce over the lifecycle, either because their initial worker mix may be more rigid by nature (as informal ties with the first hires may create barriers to labor adjustments), or because they may be founded under more unfavorable conditions (i.e., possibly more driven by necessity) than their pulled counterparts, which may constrain their post-entry growth.

Table 1. Labor market flow rates, by spin-off type (mean rates)

	Pushed Spin-offs	Pulled Spin-offs
Job Creation Rate	0.1045	0.1297
Job Destruction Rate	0.0910	0.0907
Job Reallocation Rate	0.1955	0.2204
Hiring Rate	0.1962	0.2406
Separation Rate	0.1860	0.2044
Worker Flow Rate	0.3822	0.4450
Churning Rate	0.1928	0.2316

With Figure 3, we try to understand the relationship between worker turnover and job turnover at the firm-level, by plotting hiring and separation rates on firms' net employment growth rates. To construct this figure, and following Davis et al. (2006), we have used pooled annual data at the firm-level level from 1992 to 2007 to estimate the mean hiring rate and the mean separation rate for narrow intervals of spin-offs' growth rate distribution.[11]

As expected, both hiring and separation rates increase with the magnitude of the variation of net employment at the firm-level, being almost flat for positive (negative) employment growth rates in the case of separation (hiring) rates. In particular, hires (separations) increase roughly one-for-one with job growth (loss) at expanding (contracting) spin-offs. In addition, both hiring and separation rates are lowest for zero-growth spin-offs, which imply that these firms are relatively stable regarding job growth and worker turnover. Very similar patterns were identified for the subsamples of pushed and pulled spin-offs.

[11] This method is equivalent to a least squares regression of the hiring (separation) rate on a large number of dummy variables for growth rate intervals that partition the -200 to +200 percent range. These OLS estimates are weighted by firms' average size.

Fig. 3. The relationship of spin-offs' hiring and separation rates to employment growth

Finally, Table 2 provides some information on the persistence of workers hired at entry. Column 1 summarizes the average share of "stayers" and shows that, on average, the proportion of workers hired at the start-up and remaining in the firm n years later is larger in pushed than in pulled spin-offs, but decreasing over the lifecycle in both groups of firms. This confirms that a significant part of the initial workforce leaves the firm over time.

Column 2 provides similar statistics for the subgroup of co-workers. The data confirm that the persistence rates of this type of workers are comparable to those of other workers – by the fifth year of spin-offs' activity, about 37% (31%) of those co-workers hired by pushed (pulled) spin-offs at entry still belong to the workforce. In other words, more than 60% of co-workers initially hired leave the firm during the first five years of activity.

The last column shows the relative importance of co-workers in the group of stayers. In pushed spin-offs, for each five stayers one is a co-worker hired from the parent firm. The relative presence of co-workers is much lower in pulled spin-offs, which also reflects the different importance that this group of workers assumes in both types of firms since their entry.

Table 2. Workers' persistence in the firm over firms' lifecycle

	Stayers (1)		*CW Stayers* (2)		*CW/Stayers* (3)	
	Pushed Spin-offs	Pulled Spin-offs	Pushed Spin-offs	Pulled Spin-offs	Pushed Spin-offs	Pulled Spin-offs
Year 2	80.2%	78.5%	80.7%	77.5%	22.8%	6.1%
Year 3	61.4%	57.4%	60.7%	56.7%	23.8%	5.8%
Year 4	48.9%	44.8%	47.3%	42.2%	24.6%	6.4%
Year 5	39.0%	34.7%	37.4%	31.2%	24.2%	7.0%

(1) Stayers: #Workers entering in year 1 and persisting in the firm in year n/Total # workers hired in year 1.

(2) CW Stayers: # CW hired in year 1 and persisting in year n/Total # CW hired in year 1.

(3) CW/Stayers: #CW hired in year 1 and persisting in year n/#Workers entering in year 1 and persisting in the firm in year n.

4.2 Evolution of workers' skills over firms' lifecycle

Figure 4 illustrates how the average and the dispersion of the workers' skill index have evolved over time in pushed and pulled spin-offs. We observe an upward trend in both variables during the first years of activity, which suggest that both types of spin-offs evolve, on average, towards a more skilled and diversified workforce after entry. However, this evolution seems to slow down or even reverse at more mature ages, as firms probably identify the best skill mix they need to perform their activity in the market.

Pulled spin-offs not only present a more skilled, but also a more heterogeneous, workforce than their pushed counterparts. On the other hand, while we observe some patterns of convergence over time between the two groups of spin-offs in what concerns the average skills of their employees, the same does not apply when we consider the standard deviation of workers' skills, as the differences between firms seem to remain large as they age.

Next we try to understand whether those who persist in the firm for relatively long periods (in this case, five years or more since the start-up), those who were recently hired, those who were separated, and those who come from the parent firm (co-workers) differ in terms of average skills. Table 3 summarizes the average skill index and the skill dispersion of these groups of workers, by spin-off type. Figure 5 complements the analysis by illustrating the distribution of the average skill index for different groups of workers.

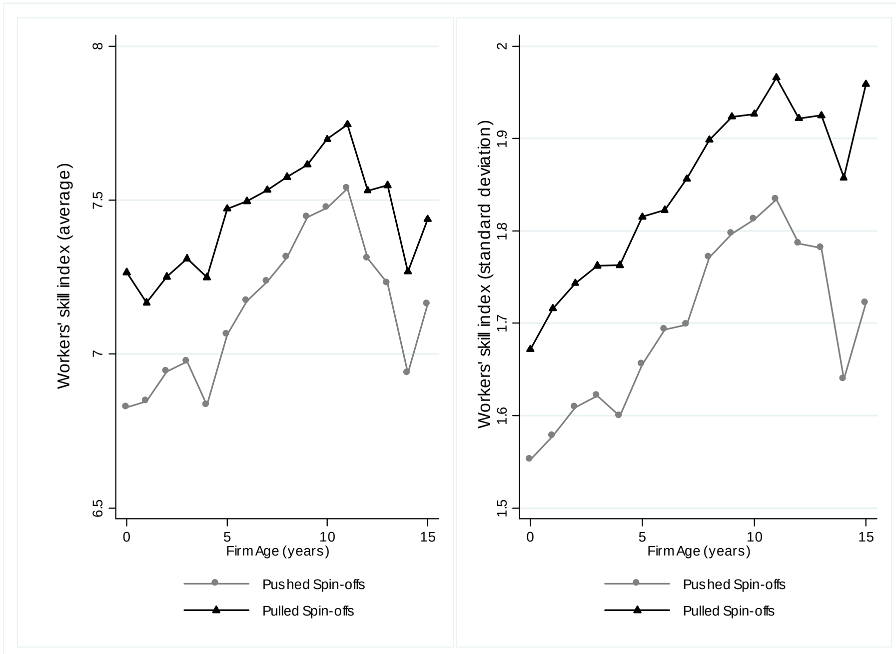

Fig. 4. Evolution of workers' skill mix over firms' lifecycle

The data confirm that stayers have a higher skill index than those who are hired over the firm lifecycle and those who leave the firm (voluntarily or involuntarily). Co-workers (particularly those persisting in the firm for longer periods) also present a higher skill index than those entering and leaving the firm over its lifecycle. This, over again, may sign some learning by firms, which seem to improve their average skill levels by holding the most skilled workers in the firm and adjusting their workforce by churning workers with lower skills on average.

Moreover, co-workers hired and retained by pulled spin-offs are much more skilled, on average, than those absorbed by their pushed counterparts. This may also suggest that, despite pulled spin-offs start with a much lower share of co-workers in their initial workforce, they seem to choose among the most skilled ones. In opposition, necessity reasons, more than skill requirements, may explain the relatively stronger presence of these workers in pushed spin-offs.

Table 3. Average skill index and average skill dispersion, by workers and spin-off type

	Pushed Spin-offs		Pulled Spin-offs	
	Average	Std. Dev.	Average	Std. Dev.
New Hires	6.401	2.289	6.495	2.330
Separations	6.628	2.377	6.718	2.243
Co-workers	6.716	2.326	7.404	2.518
Stayers (persisting $\geq$ 5 years)	7.268	2.641	7.744	2.648
Co-workers persisting $\geq$ 5 years	7.016	2.451	7.883	2.437

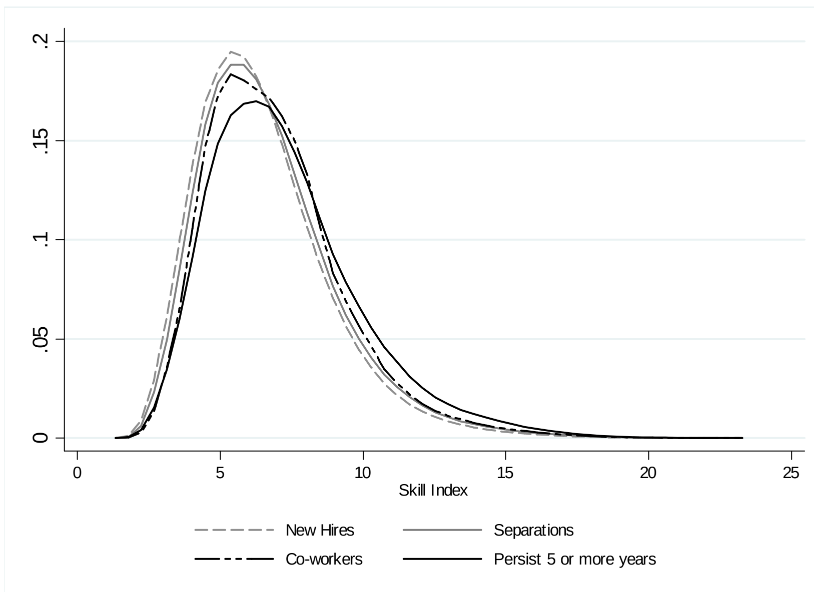

Fig. 5. Kernel density of average skill index, by worker types

Finally, given the average skill differences found between pushed and pulled spin-offs, we explore which human capital components – workers' education, experience (proxied by age) and unobserved ability – matter the most for the skill gap observed among pushed and pulled spin-offs at entry. For that purpose, we use Gelbach's (2009) unambiguous decomposition of the conditional skill gap observed in the year of their entry. We regressed each firm's *Average Workers' Skills* on their workers' average education, age and unobserved ability (measured by the person-specific fixed effect previously obtained from the wage equation with firm and worker fixed effects), controlling as well for spin-offs' size, industry and time effects. Table 4 summarizes the results.

Table 4. Conditional decomposition of the spin-offs' average skill index gap, according to spin-offs' type[a]

	Start-up year
Workers' School Years	-0.1462***
	(0.0087)
Workers' Age	0.1353***
	(0.0072)
Workers' Unobserved Heterogeneity (FE)	-0.2144***
	(0.0132)
Total Gap (Pushed vs. Pulled)	-0.2252***
	(0.0190)

Notes: [a] Decompositions based on Gelbach (2009). *** mean significant at the 1% level. The baseline model corresponds to an OLS regression with the firm's average skill index as the dependent variable, controlling for time fixed effects, spin-offs' start-up size, sector and a dummy for spin-off type. The full model additionally includes the average workers' education, age and unobserved ability as independent variables.

The results confirm that pushed spin-offs have a lower average skill index than pulled spin-offs (the gap is negative and statistically significant), even after controlling for their size, sector and time effects. The most important source of these differences seems to be workers' unobserved heterogeneity, followed by workers' education. In other words, pushed spin-offs enter with a less skilled workforce on average because their first workers have a lower person-specific effect and are less educated than those hired by pulled spin-offs at entry. In contrast, pushed spin-offs' workers are relatively more experienced, which somewhat attenuates the skill gap observed among the two types of firms.

5 Empirical Strategy

5.1 Empirical Model

The aim of the following empirical analysis is to study the impact of spin-offs' initial human capital endowments on their post-entry growth and survival. For this purpose, we start by estimating the following employment growth equation:

$$\text{Growth}_{i,t+1} = \beta_1 X_{1i,0} + \beta_2 X_{2i,t} + \beta_3 X_{3i,t} + \gamma_t + \varepsilon_{it} \tag{1}$$

where $\text{Growth}_{i,t+1} = \frac{E_{it+1} - E_{it}}{0.5*(E_{it+1}+E_{it})}$ is the employment growth rate of each spin-off i between years t and $t+1$ (with E_{it} representing total employment in firm i in year t), $X_{1i,0}$ is the vector of variables measuring the human capital endowments of spin-offs at entry (including a constant term) and β_1 is the corresponding vector of parameters of interest to be estimated.[12] Additionally, we control for a number of characteristics of firms and their BOs, which are denoted by vectors $X_{2i,t}$ and $X_{3i,t}$, respectively. Finally, γ_t represents annual time fixed effects, while ε_{it} is the error term. To account for the fact that the observations of the same spin-off over time are not independent, standard errors are corrected for clustering at the firm-level.

Firm-level variables include the type of spin-off (pushed versus pulled), two dummy variables indicating whether or not the spin-off is established in the same location (county) and in the same industry of the parent firm, in addition to spin-offs' start-up size, age (and its square), productivity (measured by the log of sales per worker) and an indicator variable controlling for firm location in an urban region.

Regarding BOs' characteristics, we control for their general and specific human capital (BOs' age, education, entrepreneurial experience and industry-specific experience). Furthermore, we include two dummy variables indicating whether there are two or more BOs in the firm (shared ownerships) and whether the spin-off suffers any type of ownership change in the subsequent year. This last aspect has been recurrently neglected by previous studies on new firm performance, though seminal theories on entrepreneurship and BOs' turnover recognize that ownership transfers may be common, as the entrepreneur and the firm are two different parts that should be perfectly matched (Holmes and Schmitz, 1995, 1996). In

[12] When defining our growth measure, we follow previous influential studies (e.g., Davis and Haltiwanger, 1990; 1992; Davis et al., 1996; Burgess et al., 2000; Haltiwanger et al., 2013) who highlight the importance of taking into account the current average size in the denominator in order to mitigate the effects of regression to the mean and avoid any bias. While using base year size could yield a negative bias, using the end year size could produce a positive bias. The current average size – $0.5 * (E_{i,t+1} + E_{i,t})$ – is, thus, a satisfactory alternative.

our data, about 30% of all spin-offs under analysis suffer at least one change in their "entrepreneurial team" during the lifecycle, so we also control for these ownership changes.[13] A detailed description of all these variables can be found in Table A.I, in the Appendix.

However, a relevant problem in new firm growth studies is the possibility of selection bias, given that selection is a function of the firm's efficiency in competition with other similar firms (Delmar et al., 2013). In particular, and according to the classic results of Nelson and Winter (1982), the most efficient (or the "fittest") firms normally survive and grow, while less viable firms (which typically correspond to smaller and more slowly growing firms) are systematically selected out of the market. Consequently, spin-offs' growth rates are only observed for the subset of surviving firms and, for this reason, pooled OLS estimation results may be inconsistent if firm exit and employment growth are not independent phenomena.

We, thus, specify a two-equation Heckman-type model in order to correct for selection bias on spin-offs' exit.[14] Formally, we have an outcome (growth) equation and a selection (exit) equation, as follows:

$$\text{Growth}_{i,t+1} = \begin{cases} \beta_1 X_{1i,0} + \beta_2 X_{2i,t} + \beta_3 X_{3i,t} + \gamma_t + \varepsilon_{it} & \text{if } y^*_{i,t+1} > 0 \\ - & \text{if } y^*_{i,t+1} \leq 0 \end{cases} \tag{2}$$

$$Exit_{i,t+1} = \begin{cases} 0 \text{ if } y^*_{i,t+1} > 0 \\ 1 \text{ if } y^*_{i,t+1} \leq 0 \end{cases} \tag{3}$$

where $y^*_{i,t+1} = \beta_1 X_{1i,0} + \beta_2 X_{2i,t} + \beta_3 X_{3i,t} + \beta_4 X_{4i,t} + \gamma_t + \theta_{it}$ represents a latent variable measuring the differential in spin-offs' utility (or profit) between remaining active or exiting the market. By allowing the error terms ε_{it} and θ_{it} to be correlated, we are able to correct for the possible non-randomness of the selected sample of spin-offs.

To improve the robustness of our estimation, we follow the two-step estimator and use a vector of industry-level characteristics ($X_{4i,t}$) as exclusion restrictions for a more robust identification. This vector includes the industry's minimum efficient scale, concentration, growth, agglomeration and entry rates (see Table A.I for a detailed description of these variables). While industry-specific characteristics seem to consistently explain differences

[13] The changes in the entrepreneurial team may take several forms. Either the founder(s) may have transferred the firm to other BO(s) during the firm lifecycle (this is the most frequent case, with the founder/current BO being replaced by a new one), or a new BO may join the current entrepreneurial team after the firm has been established (for instance, when the firm is established as a single-owned firm and then changes to a status of shared ownership), or even one of the BOs may leave the current entrepreneurial team, which may be composed by two or more BOs. Moreover, multiple ownership changes may occur over firms' lifecycle, though this is less frequent. Among the 15,037 spin-offs suffering ownership changes in our dataset, 64% of them suffer only one ownership change during the time period under observation.

[14] The Heckman's (1979) procedure has been used by several recent studies on the relationship between firm growth and survival (e.g., Czarnitzk and Delanote, 2012; Delmar et al., 2013; Koch et al., 2013; Huber et al., 2014).

in survival rates across firms, these variables typically add limited explanatory power in firm growth studies (see the surveys by Manjón-Antolín and Arauzo-Carod (2008) on firm survival, and Coad (2007, 2009) on firm growth). Furthermore, in our data, industry-level variables can be shown to have a significant effect on firm exit and a negligible effect on spin-offs' employment rates.

We have then repeated this procedure to estimate similar equations for particular dimensions of spin-offs' worker flows, namely Hiring Rates and Separation Rates, aiming at understanding how the characteristics of spin-offs' initial workforce may influence these post-entry labor adjustments.

5.2 Empirical Results

Table 4 reports and compares the results obtained from the estimation of pooled OLS employment growth equation and Heckman two-step model. Some descriptive statistics on the variables included in these estimations can be found in Table A.II, in the Appendix. Besides the differences in their initial workforce, these statistics also reveal that pushed spin-offs are more frequently established in the same location and in the same industry where the parent firm operated before. This group of firms also starts at a slightly larger scale than pulled spin-offs, which may be achieved through the absorption of a more significant number of co-workers at entry. Though their BOs are, on average less educated, they seem to be more experienced than pulled spin-offs' BOs. Finally, both shared ownerships and ownership changes are relatively more frequent in pushed than in pulled spin-offs.

The empirical results confirm that there is a significant selection bias in the sample due to firm exit. We found a negative and significant correlation between the error terms of the two equations, which attests that firm exit and growth are not independent. Instead, exiting firms tend to suffer a significant downsizing before closing down operations, in line with the so-called "growth of the fitter hypothesis" of evolutionary models (e.g, Jovanovic, 1982; Nelson and Winter, 1982).

Moreover, the results show that not controlling for spin-offs' selection on exit has important implications regarding the impact of the initial human capital endowments on post-entry growth. When accounting for selection bias in the sample, only the *Skill Dispersion* of the initial workforce exerts a significant effect on spin-offs' employment growth. The results suggest that starting with a more heterogeneous workforce in terms of skills reduces employment growth, besides increasing firm exit rates.

The other measures of initial human capital do not seem to significantly affect post-entry growth after controlling for spin-offs' exit. Pooled OLS estimation results would suggest that pushed spin-offs grow less than their pulled counterparts, and that entering with a larger share of co-workers would penalize firms' post-entry growth. However, the estimation results for the selection (exit) equation point out that, first, pushed spin-offs have slightly lower exit rates than pulled spin-offs, and second, that the presence of co-workers reduces the risk of exit. Overall, the effects of these variables on firm survival seem to cancel out their potential negative effects on post-entry growth.

Regarding the effects of workers' average skills, starting with a more skilled workforce seems to decrease firm exit rates, while no important effects seem to arise in terms of growth. The results, overall, suggest that initial human capital endowments are more important for firm survival than for firm post-entry growth. Though initial workforce characteristics seem to influence both firm growth and exit individually, when we control for the fact that both processes are negatively correlated, most of the effects on spin-offs' growth actually vanish.[15]

The results for the remaining variables included in estimations are, overall, in line with the literature. Spin-offs established in the same location (county) of the parent firm survive longer and present higher post-entry growth rates, as they may benefit from prior experience in the region and have specific knowledge, networks and contacts that help them to perform better than those who are established in a different region. Firms entering at a larger scale grow less, but overcome the so-called liability of smallness – suffering, thus, lower exit rates. More productive firms (in terms of sales per worker) grow more and survive longer on average.

Regarding the characteristics of BOs, both general and specific human capital of entrepreneurs seem to improve spin-offs' survival, while the effects on post-entry growth are almost negligible. Sharing the ownership of the business with other BO(s) is found to improve both growth and survival prospects at the firm-level. Ownership changes, in turn, seem to have negative effects on both performance measures. While the literature has been suggesting that founder or BOs turnover are likely to be motivated by perceived mismatches between business quality and entrepreneurs' ability (e.g., Holmes and Schmitz, 1995, 1996), evidence on the effects of these ownership transfers is still limited and inconclusive. Chen and Thompson (2013), for instance, found that business transfers are associated with higher growth rates among surviving firms, but also with higher firm exit rates.

[15] As a robustness check, we have estimated the Heckman two-step model for the separate samples of spin-offs operating in Manufacturing and Services, where workers' initial skills might play different roles or assume a different importance. The results are summarized in Table A.III in the Appendix and remain consistent with the results previously obtained for all spin-offs, though the effects of the variables of interest are found to be more significant for spin-offs operating in Services. We have also re-estimated the Heckman two-step model with sample weights, using spin-offs' survival time as the weighting variable. The estimated effects of spin-offs' initial human capital measures remain qualitatively unchanged, being summarized in Table A.IV.

Table 4. Estimation results for employment growth and survival (Portugal, 1992-2007)

	Pooled OLS	Heckman Two-step model	
	Employment growth	Employment growth	Firm exit
Pushed Spin-off	-0.0063***	0.0112	-0.0265**
	(0.0018)	(0.0133)	(0.0123)
Average skill index at entry	0.0003	0.0005	-0.0145***
	(0.0006)	(0.0050)	(0.0039)
Skill dispersion at entry	-0.0020**	-0.0181***	0.0170***
	(0.0008)	(0.0064)	(0.0055)
Share of co-workers at entry	-0.0138***	0.0254	-0.1082***
	(0.0041)	(0.0364)	(0.0280)
Same location of PF	0.0588***	0.1569**	-0.2793***
	(0.0062)	(0.0629)	(0.0230)
Same sector of PF	0.0013	-0.0025	-0.0198
	(0.0019)	(0.0131)	(0.0129)
Start-up size	-0.0190***	-0.0718***	-0.0504***
	(0.0018)	(0.0138)	(0.0091)
Urban	0.0007	-0.0215	0.0510***
	(0.0017)	(0.0156)	(0.0111)
Age	-0.0185***	-0.0094	-0.0379***
	(0.0010)	(0.0107)	(0.0069)
Age squared	0.0010***	0.0011**	0.0012***
	(0.0001)	(0.0005)	(0.0005)
Firm sales per worker	0.0388***	0.0442***	-0.0227***
	(0.0011)	(0.0072)	(0.0053)
BOs' age	-0.0013***	0.0008	-0.0019***
	(0.0001)	(0.0007)	(0.0007)
BOs' schooling years	-0.0006**	-0.0004	-0.0037**
	(0.0003)	(0.0017)	(0.0015)
BOs' entrepreneurial experience	-0.0014***	-0.0006	-0.0060**
	(0.0004)	(0.0034)	(0.0031)
BOs' industry experience	0.0016***	0.0090***	-0.0058***
	(0.0003)	(0.0024)	(0.0021)
Shared Ownership	-0.0125***	0.1207*	-0.2801***
	(0.0018)	(0.0630)	(0.0126)
Ownership Change	0.0066**	-0.0911***	0.1176***
	(0.0027)	(0.0296)	(0.0151)

(It continues in the next page)

Table 4. Estimation results for employment growth and survival (Portugal, 1992-2007)

(cont.)	Pooled OLS	Heckman Two-step model	
	Employment growth	Employment growth	Firm exit
MES	-	-	0.0382***
	-	-	(0.0038)
HH Index	-	-	-1.5499***
	-	-	(0.5880)
Industry Growth	-	-	-0.0933*
	-	-	(0.0519)
Industry Agglomeration	-	-	0.6501***
	-	-	(0.1412)
Industry Entry Rate	-	-	0.4849***
	-	-	(0.1875)
Constant	-0.2717***	0.9530*	-1.6814***
	(0.0203)	(0.5172)	(0.0799)
Inverse Mills Ratio	-	-0.5569**	-
	-	(0.2594)	-
Observations	131,734	143,911	

Notes: Time-varying independent variables are measured in t-1. All the models include time dummies. Both employment growth equations also include 2-digit industry dummies. Firm-cluster robust standard errors in parentheses. *, ** and *** denote significant at 10%, 5% and 1%, respectively. The estimated correlation between the errors of employment growth and firm exit equations is negative and significantly different from zero ($\widehat{\rho}$ =-0.8332).

As expected, industry environment significantly influences spin-offs' survival. Exit rates tend to be higher in industries where the minimum efficient scale, employment agglomeration and entry rates are also higher – and where competition is stronger. In contrast, firms operating in more concentrated industries, by probably having higher market power, are found to face lower risks of exit.

Finally, given that firm-level employment growth is the result of firms' adjustments in their workforce through different combinations of hires and separations, we explore how the characteristics of spin-offs' initial workforce might be associated with these particular worker flows. We present a summary of the results obtained from Heckman two-step procedure in Table 5.

Table 5. Estimation results for spin-offs' hiring and separation rates, Heckman two-step model (Portugal, 1992-2007)

	Hiring Rates	Separation Rates
Pushed Spin-off	-0.0105	-0.0111
	(0.0073)	(0.0117)
Average skill index at entry	-0.0016	-0.0020
	(0.0028)	(0.0044)
Skill dispersion at entry	0.0010	0.0178***
	(0.0035)	(0.0056)
Share of co-workers at entry	-0.0571***	-0.0728**
	(0.0203)	(0.0320)
Inverse Mills Ratio	-0.0558	0.4589**
	(0.1510)	(0.2293)
Observations	143,911	143,911

Notes: All the models include the firm-level and BO-level variables included in the specification of the employment growth equation presented in Table 4, in addition to time dummies and industry dummies. *, ** and *** denote significant at 10%, 5% and 1%, respectively. The estimated error correlation between the error terms is equal to -0.2073 in the case of hiring rates (not significantly different from zero) and 0.8055 in the case of separation rates (statistically different from zero at the 1% level).

As expected, firm exit is negatively (positively) correlated with hiring (separation) rates at the firm-level. Moreover, these additional results confirm that the skill dispersion of the initial workforce plays a significant negative effect on post-entry growth by increasing firm-level separation rates. In addition, the estimations also indicate that spin-offs hiring a larger share of co-workers at the time of entry not only tend to hire less new workers, as also present lower separation rates. Overall, labor adjustments in these firms seem to be less frequent, either because they start with a more stable (or rigid) workforce – which may make subsequent adjustments more costly –, or because they identify their best matches earlier than other firms, possibly owing to the past relationship between co-workers and spin-offs' founders at the parent firm.

Finally, despite pulled spin-offs unconditionally present more remarkable adjustments in their workforce over the lifecycle, the differences between pushed and pulled spin-offs' hiring and separation rates become, over again, insignificant when we correct for firm selection on exit. Actually, after taking into account several characteristics of workers, BOs, firms and industries, we find no evidence that pulled spin-offs outperform their pushed counterparts –

neither in growth, nor in survival –, as some recent studies have proposed (e.g., Buenstorf, 2009; Bruneel et al., 2013). Though pushed spin-offs may be mostly established under more unfavorable conditions (i.e., as a reaction to deteriorating job conditions and without any type of support from the parent company), these firms seem to be able to perform as well as spin-offs driven by pull-nature factors.

6 Concluding Remarks

In this paper we have analyzed how the post-entry employment dynamics and survival of pushed and pulled spin-offs were associated to the characteristics of the workers employed at entry. Our empirical results suggest that spin-offs' survival is closely related to the human capital endowments presented at entry. Firms employing a more skilled workforce at the start-up and a higher share of co-workers absorbed from the parent firm face lower exit rates. In contrast, skill dispersion at entry increases firm exit rates and significantly reduces post-entry employment growth, by increasing firms' separation rates.

Overall, the data suggest that spin-offs adjust their workforce over the lifecycle by preserving the most skilled workers, and by hiring and separating the less skilled employees, as those staying in the firm for longer periods are, on average, more skilled than those who enter and exit the firm (voluntarily or not) over time. Additionally, worker flows are lower in spin-offs entering with a more significant share of co-workers in the initial workforce. The choice of the very first employees is, hence, shown to have long-term effects on spin-offs' labor adjustments, either due to informal ties developed between the initial workers and spin-offs' founders, or due to firing restrictions.

In summary, our analysis indicates that the initial human capital endowments may be important determinants of spin-offs' post-entry performance. Labor adjustments may be difficult, either due to strict employment legislation or by firm natural inertia. In view of that, start-up conditions – namely the skills of the initial workforce and the firms' early ability of screening heterogeneous workers – may play a crucial role in the post-performance of new firms, especially in countries where strict employment legislation restricts labor adjustments and, consequently, firms' ability to respond to market changes in a short-time horizon.

Finally, the paper offers possible avenues for future extensions that may be of interest for both labor economics and industrial organizations researchers. From the point of view of labor economics, this study highlights the role that workers' human capital may play in worker turnover and labor reallocation processes. From the point of view of industrial economics, the results shed new light on the significant link between firm performance and workers' characteristics, and on the relevance of start-up conditions – in particular, the role of spin-offs' initial human capital endowments – for post-entry employment growth and survival. Last but not least, the results here presented may also motivate further research on the post-entry performance differences between pushed (necessity) and pulled (opportunity) spin-offs.

References

[1] Abowd, J. M., Corbel, P., Kramarz, F. (1999a), "The entry and exit of workers and the growth of employment: An analysis of French establishments", *The Review of Economics and Statistics*, 81(2), 170-187.

[2] Abowd, J. M., Kramarz, F., Margolis, D. (1999b), "High wage workers and high wage firms". *Econometrica*, 67(2), 251-334.

[3] Agarwal, R., Campbell, B., Franco, A. M., Ganco, M. (2011), "What do I take with me: the impact of transfer and replication of resources on parent and spin-out performance", Center for Economic Studies, U.S. Census Bureau Working Papers, Working Paper No. 11-06.

[4] Andersson, M., Klepper, S. (2013), "Characteristics and performance of new firms and spinoffs in Sweden", *Industrial and Corporate Change*, 22(1), 245-280.

[5] Audretsch, D. B., Keilbach, M. (2005), "The mobility of economic agents as conduits of knowledge spillovers". In D. Fornahl, C. Zellner and D. B. Audretsch (Eds.), The role of labour mobility and informal networks for knowledge transfer, International Studies in Entrepreneurship, Springer, Volume 6, pp. 8-25.

[6] Barney, J. (2001), "Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view", *Journal of Management*, 27(6), 643-650.

[7] Bruneel, J., de Velde, E. V., Clarysse, B. (2013), "Impact of the type of corporate spin-off on growth", *Entrepreneurship Theory & Practice*, 37(4), 943-959.

[8] Buenstorf, G. (2009), "Opportunity spin-offs and necessity spin-offs", *International Journal of Entrepreneurial Venturing*, 1(1), 22-40.

[9] Burgess, S., Lane, J., Stevens, D. (2000), "The reallocation of labour and the lifecycle of firms", *Oxford Bulletin of Economics and Statistics*, 62, Special Issue "Labour Markets Observed", 885-907.

[10] Chen, J., Thompson, P. (2013), "New firm performance and the replacement of founder-CEOs", mimeo, Copenhagen Business School.

[11] Coad, A. (2007), "Firm growth: A survey", Papers on Economics and Evolution, Paper No. 0703. Max Planck Institute of Economics - Evolutionary Economics Group.

[12] Coad, A. (2009), *The growth of firms: A survey of theories and empirical evidence*. Cheltenham: Edward Elgar Publishing Ltd.

[13] Crook, T. R., Todd, S. Y., Combs, J. G., Woehr, D. J., Ketchen, D. J. (2011), "Does human capital matter? A meta-analysis of the relationship between human capital and firm performance", *Journal of Applied Psychology*, 96(3), 443-456.

[14] Czarnitzki, D., Delanote, J. (2013), "Young innovative companies: the new high-growth firms?", Industrial and Corporate Change, 22(5), 1315-1340.

[15] Davis, S. J., Haltiwanger, J. (1990), "Gross job creation and destruction: microeconomic evidence and macroeconomic implications", NBER Macroeconomics Annual, vol. 5, 123-168.

[16] Davis, S. J., Haltiwanger, J. (1992), "Gross job creation, gross job destruction, and employment reallocation", *The Quarterly Journal of Economics*, 107(3), 819-863.

[17] Davis, S. J., Haltiwanger, J., Schuh, S. (1996), Job Creation and Destruction, MIT Press, Cambridge, Massachusetts.

[18] Davis, S. J., Faberman, R. J., Haltiwanger, J. (2006), "The flow approach to labor markets: New data sources and micro-macro links", Journal of Economic Perspectives, 20(3), 3-26.

[19] Davis, S., J., Haltiwanger, J., Jarmin, R. S., Krizan, C. J., Miranda, J., Nucci, A., Sandusky, K. (2009), "Measuring the dynamics of young and small businesses: Integrating the employer and nonemployer universes", in T. Dunne, J. Bradford Jensen, and M. J. Roberts (Eds.), Producer Dynamics: New Evidence from Micro Data, pp. 329 – 366, National Bureau of Economic Research, University of Chicago Press.

[20] Delmar, F., McKelvie, A.,Wennberg, K. (2013), "Untangling the relationships among growth, profitability and survival in new firms", Technovation, 33(8-9), 276-291.

[21] Dick, J. M. H., Hussinger, K., Blumberg, B., Hagedoorn, J. (2013), "Is success hereditary? Evidence on the performance of spawned ventures", *Small Business Economics*, 40(4), 911-931.

[22] Franco, A. M., Filson, D. (2006), "Spin-outs: knowledge diffusion through employee mobility", *Rand Journal of Economics*, 37(4), 841-860.

[23] Gelbach, J. B. (2009), "When do covariates matter? And which ones, and how much?". Department of Economics, Working Paper 2009-07, University of Arizona, Tucson.

[24] Geroski, P. A., Mata, J., Portugal, P. (2010), "Founding conditions and the survival of new firms", *Strategic Management Journal*, 31(5), 510-529.

[25] Geroski, P., Mazzucato, M. (2002), "Learning and the sources of corporate growth", *Industrial and Corporate Change*, 11(4), 623-644.

[26] Gibbons, R., Katz, L. (1991), "Layoffs and lemons", *Journal of Labor Economics*, 9(4), 351-380.

[27] Guimarães, P., Portugal, P. (2010), "A simple feasible alternative procedure to estimate models with high-dimensional fixed effects", *The Stata Journal*, 10(4), 628-649.

[28] Haltiwanger, J. C., Jarmin, R. S., Miranda, J. (2013), "Who creates jobs? Small versus Large versus Young", *The Review of Economics and Statistics*, 95(2), 347-361.

[29] Haltiwanger, J. C., Lane, J. I., Spletzer, J. R. (1999), "Productivity Differences across Employers: The Roles of Employer Size, Age, and Human Capital", *American Economic Review*, 89(2), 94-98.

[30] Haltiwanger, J. C., Lane, J. I., Spletzer, J. R. (2007), "Wages, productivity and the dynamic interaction of businesses and workers", *Labour Economics*, 14(3), 575-602.

[31] Hamermesh, D. (2008), "Fun with matched firm-employee data: Progress and road maps", *Labour Economics*, 15(4), 663-673.

[32] Heckman, J. J. (1979), "Sample selection bias as a specification error", Econometrica, 47(1), 153-162.

[33] Holmes, T. J., Schmitz, J. A. (1995), "On the turnover of business firms and business managers", *Journal of Political Economy*, 103(5), 1005-1038.

[34] Holmes, T. J., Schmitz, J. A. (1996), "Managerial tenure, business age and small business turnover", *Journal of Labor Economics*, 14(1), 79-99.

[35] Huber, P., Oberhofer, H., Pfaffermayry, M. (2014), "Job creation and the intra-distribution dynamics of the firm size distribution", Industrial and Corporate Change, 23(1), 171-197.

[36] Ilmakunnas, P., Ilmakunnas, S. (2011), "Diversity at the workplace: whom does it benefit?, *De Economist*, 159(2), 223-255.

[37] Ilmakunnas, P., Maliranta, M., Vainioma, J. (2004), "The roles of employer and employee characteristics for plant productivity", *Journal of Productivity Analysis*, 21(3), 249–276.

[38] Iranzo, S., Shivardi, F., Tosetti, E. (2008), "Skill dispersion and firm productivity: An analysis with employer-employee matched data", *Journal of Labor Economics*, 26(2), 247-285.

[39] Jovanovic, B. (1979), "Job matching and the theory of turnover", *Journal of Political Economy*, 87(5), 972–990.

[40] Jovanovic, B. (1982), "Selection and the evolution of industry", Econometrica, 50(3), 649-670.

[41] Jovanovic, B. (1984), "Matching, turnover, and unemployment", *Journal of Political Economy*, 92(1), 108–122.

[42] Koch, A., Späth, J., Strotmann, H. (2013), "The role of employees for post-entry firm growth", *Small Business Economics*, 41(3), 733-755.

[43] Kremer, M. (1993), "The O-ring theory of economic development", *Quarterly Journal of Economics*, 108(3), 551-575.

[44] Lazear, E. P. (1999), "Globalisation and the market for team-mates", *The Economic Journal*, 109(454), 15-40.

[45] Lazear, E. P., Oyer, P. (2007), "Personnel Economics", NBER Working Paper No. 13480.

[46] Leitch, C., Hill, F., Neergaard, H. (2010), "Entrepreneurial and business growth and the quest for a "Comprehensive Theory": Tilting at windmills?", *Entrepreneurship Theory & Practice*, Special Issue "Entrepreneurial and Business Growth", 34(2), 249-260.

[47] Lopez-Garcia, P., Puente, S. (2012), "What makes a high-growth firm? A dynamic probit analysis using Spanish firm-level data", *Small Business Economics*, 39(4), 1029-1041.

[48] Mamede, R. (2008), "Toward an integrated approach to industry dynamics and labor mobility", *Industrial and Corporate Change*, 18(1), 139-163.

[49] Manjón-Antolín, M. C., Arauzo-Carod, J. (2008), "Firm survival: methods and evidence", *Empirica*, 35(1), 1-24.

[50] Martins, P. (2008), "Dispersion in wage premiums and firm performance", *Economics Letters*, 101(1), 63-65.

[51] Mata, J., Portugal, P. (2002), "The survival of new domestic and foreign-owned firms", *Strategic Management Journal*, 23(4), 323-343.

[52] McKelvie, A., Wiklund, J. (2010), "Advancing firm growth research: A focus on growth mode instead of growth rate", *Entrepreneurship Theory & Practice*, Special Issue "Entrepreneurial and Business Growth", 34(2), 261-288.

[53] Messina, J., Vallanti, G. (2007), "Job flow dynamics and firing restrictions: Evidence from Europe", *The Economic Journal*, 117(521), 279-301.

[54] Muendler, M., Rauch, J. E., Tocoian, O. (2012), "Employee spinoffs and other entrants: Stylized facts from Brazil", *International Journal of Industrial Organization*, 30(5), 447-458.

[55] Nelson, R., Winter, S. (1982), An evolutionary theory of economic change. Cambridge, MA: Belknap Press.

[56] OECD, Organisation for Economic Cooperation and Development (2013a), *Financing SMEs and Entrepreneurs 2013: An OECD Scoreboard*. OECD Publishing.

[57] OECD, Organisation for Economic Cooperation and Development (2013b), *Helping displaced workers back into jobs by maintaining and upgrading their skills*. Analytical Report, Employment Analysis and Policy Division, Directorate for Employment, Labour and Social Affairs.

[58] OECD, Organisation for Economic Cooperation and Development (2010), *High-Growth Enterprises: What Governments Can Do to Make a Difference*. OECD Studies on SMEs and Entrepreneurship, OECD Publishing.

[59] Østergaard, C. R., Timmermans, T., Kristinsson, K. (2011), "Does a different view create something new? The effect of employee diversity on innovation", *Research Policy*, 40(3), 500-509.

[60] Parrotta, P., Pozzoli, D., Pytlikova, M. (2012), "Does labor diversity affect firm productivity?", IZA Discussion Papers, Paper No. 6973.

[61] Portela, M. (2001), "Measuring skill: a multi-dimensional índex", *Economics Letters*, 72(1), 27-32.

[62] Rauch, A., Frese, M., Utsch, A. (2005), "Effects of human capital and long-term human resources development and utilization on employment growth of small-scale businesses: A causal analysis", *Entrepreneurship Theory & Practice*, 29(6), 681-698

[63] Rocha, V., Carneiro, A., Varum, C. A. (2013), "Where do spin-offs come from? Start-up conditions and the survival of pushed and pulled spin-offs", mimeo.

[64] Song, J., Almeida, P., Wu, G. (2003), "Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer?", *Management Science*, 49(4), 351-365.

Appendix

Table A.I. Description of variables

Initial human capital endowments	
Workers' average skills at entry	Average level of workers' skill index, by firm, at the start-up.
Skill dispersion at entry	Standard deviation of workers' skill index, by firm, at the start-up.
Share of co-workers at entry	Total number of co-workers in the workforce in firm *i* at the start-up/Total number of employees in firm *i* at the start-up.
Firm-level characteristics	
Pushed Spin-off	Dummy variable equal to 1 if the firm is a pushed spin-off, 0 otherwise.
Firm start-up size	Number of employees of firm *i* at entry, in logs.
Firm age	Years elapsed since the start-up.
Firm Productivity	Sales per worker, in logs. Sales are in constant prices of 2005.
Urban region	Dummy variable equal to 1 if the spin-off is located in the districts of Porto or Lisbon, 0 otherwise.
Same location of the parent firm	Dummy variable equal to 1 if the spin-off is located in the same county of the parent firm, 0 otherwise.
Same industry (2d) of the parent firm	Dummy variable equal to 1 if the spin-off operates in the same 2-digit industry of the parent firm, 0 otherwise.
Business-Owners' characteristics	
BOs' age[a]	Business-owners' age, in years, in the reference period.
BOs' education[a]	Business-owners' schooling years in the reference period.
BOs' entrepreneurial experience[a]	Total number of years of experience as BOs in the reference period.
BOs' industry experience[a]	Total number of years of experience in the 2-digit industry (as BO or paid employee) in the reference period.
Shared Ownership	Dummy variable equal to 1 if the spin-off has 2 or more BOs in the reference period, 0 otherwise.
Ownership change	Dummy variable equal to 1 if the spin-offs' entrepreneurial team changes in the next year, 0 otherwise.
Industry-level characteristics[b]	
MES (Minimum Efficient Scale)	Median number of employees in the 2-digit industry in each year.
HH index	Sum of the squared share of each firm's employment in the total 2-digit industry's employment in each year.
Industry growth	Annual percentage change in 2-digit employment.
Industry agglomeration	Share of 2-digit industry's employment in the total employment in the country, in each year.
Entry rate	Ratio of total firm entries over the total number of incumbent firms in the 2-digit industry, by year.

[a] Whenever the spin-offs has two or more BOs, these variables measure their average age, education and years of experience, respectively as BOs or in the industry. [b] These variables are only included in the selection (exit) equation.

Table A.II. Descriptive statistics (Portugal, All spin-offs, 1992-2007)

	All Spin-offs		Pushed Spin-offs		Pulled Spin-offs	
	Average	Std. Dev.	Average	Std. Dev.	Average	Std. Dev.
Workers' Skills at entry						
Workers' average skills	7.1255	2.3348	6.8266	2.1824	7.2649	2.3898
Skill dispersion	1.6297	1.1594	1.5526	1.0734	1.6717	1.2016
Share of co-workers	0.0982	0.2016	0.1947	0.2584	0.0536	0.1493
Firm-level Variables						
Same location of PF (%)	0.8679	0.3386	0.9123	0.2828	0.8474	0.3596
Same industry (2d) of PF (%)	0.4908	0.4999	0.6330	0.4820	0.4251	0.4944
Start-up size (logs)	0.9798	0.7763	1.1913	0.8305	0.8821	0.7296
Firm age (y)	4.5794	3.5117	4.6667	3.5303	4.5354	3.5015
Urban region (%)	0.4055	0.4910	0.3992	0.4897	0.4085	0.4916
Sales per worker (logs)	10.513	1.1028	10.495	1.0944	10.521	1.107
BO-level variables						
BOs' age (y)	39.832	9.1752	40.631	9.2024	39.428	9.1349
Bos' education (y)	8.4169	4.2954	7.8060	4.0427	8.7247	4.3851
BO's entrepreneurial exp. (y)	3.5327	2.7148	3.7756	2.7959	3.4103	2.6646
BOs' industry (2d) exp. (y)	4.5175	3.8538	5.1302	3.9344	4.2088	3.7749
Shared ownership (%)	0.3199	0.4665	0.3851	0.4866	0.2871	0.4524
Ownership changes (%)	0.1385	0.3455	0.1454	0.3525	0.1351	0.3418
Industry-level variables						
MES	3.4949	1.6253	3.6682	1.7216	3.4076	1.5674
HH index	0.0031	0.0110	0.0028	0.0097	0.0032	0.0116
Industry growth	0.0385	0.1521	0.0333	0.1547	0.0412	0.1507
Industry agglomeration	0.0868	0.0404	0.0863	0.0410	0.0871	0.0401
Entry rate	0.1291	0.0410	0.1253	0.0411	0.1310	0.0408

Notes: PF means Parent Firm. y means years. Regarding BOs' age, education and experience variables, whenever the firm has two or more BOs, these variables correspond to the average years of age, education and experience of all BOs in the firm.

Table A.III. Heckman two-step estimation results (Manufacturing and Services samples)

	Manufacturing		Services	
	Employment growth	Firm exit	Employment growth	Firm exit
Pushed Spin-off	0.0101	-0.0470*	0.0057	-0.0158
	(0.0301)	(0.0275)	(0.0132)	(0.0157)
Average skill index at entry	-0.0016	-0.0302***	-0.0014	-0.0179***
	(0.0137)	(0.0104)	(0.0035)	(0.0042)
Skill dispersion at entry	-0.0093	0.0051	-0.0100*	0.0158**
	(0.0151)	(0.0156)	(0.0053)	(0.0063)
Share of co-workers at entry	-0.0541	-0.0711*	0.0211	-0.1131***
	(0.0574)	(0.0348)	(0.0334)	(0.0378)
Inverse Mills Ratio	-0.6845**	-	-0.1577**	-
	(0.3413)	-	(0.0805)	-
Observations	28,488		90,519	

Notes: *, ** and *** denote significant at 10%, 5% and 1%, respectively. The coefficients on the firm, BOs and industry variables are not reported to save space, being available upon request.

Table A.IV. Heckman maximum-likelihood estimation results, weighted by spin-offs' survival time

	Employment growth	Firm exit
Pushed Spin-off	0.0176	-0.0129
	(0.0147)	(0.0128)
Average skill index at entry	0.0075	-0.0127***
	(0.0046)	(0.0039)
Skill dispersion at entry	-0.0223***	0.0201***
	(0.0061)	(0.0056)
Share of co-workers at entry	0.0255	-0.1059***
	(0.0323)	(0.0290)
Observations	143,911	

Notes: This model corresponds to the same model presented in Table 4, but using maximum likelihood and sampling weights, as weighted estimation is only possible under maximum likelihood estimation. *** denotes significant at 1%. The estimated correlation between the errors is statistically significant at the 1%, and equal to -0.8936. The coefficients of firm, BOs and industry variables are not reported to save space, being available upon request.