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Mobility of Skills and Ideas

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October 2011

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This paper examines and tests how the composition of human capital that workers acquire on-the-job determines the decision to found spinoffs and the know-how that entrepreneurs exploit in the new firm. I argue that given the different degree of specialisation in small and large firms, entrepreneurs emerging from small firms transfer knowledge from more diverse aspects of the business and create spinoffs more related to the main activity of the incumbent firm. Workers in large firms, however, benefit from higher returns to human capital that increase their opportunity costs to switch to an occupation that requires a different combination of skills. Since becoming an entrepreneur implies performing multiple tasks and makes part of their specialised skills unutilised, the minimum quality of the business idea at which they are willing to reveal the discovery is higher and, therefore, entrepreneurs emerging from large firms are of highest quality.

Keywords: Spinoffs ; enrepreneurship ; human caital ; on-the-job learning ; firm performance

Jel codes: L25 ; L26 ; J31 ; J33 ; M52 ; M54

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1 Introduction

Since Arrow (1962), labour mobility is considered to spread knowledge across firms, especially when this consists of intangible information and is embodied in worker's skills (Kim and

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Marschke, 2005). This paper aims to explain how the human capital that workers acquire on-the-job determines their decision to found spinoffs and the knowledge that entrepreneurs exploit in the new firm.

This approach provides insight into the established empirical regularity of entrepreneurs exploiting business ideas they encountered while working for an established firm. For instance, as pointed out by Cooper (1985) 75% of the ideas developed in technical start-ups are closely related to their incumbent organisation, a finding similar to that of Bhide (2000) who asserts that "71 percent of the firms were founded by people who replicated or modified an idea encountered in their previous employment" (p.94). Many examples to illustrate the spawning activity of established firms are taken from Silicon Valley, Massachusetts, responding to the prominent spinoff activity in the semiconductor industry in this region. Specifically, from over 100 ventures entering the industry from 1957 to 1986, nearly all of them were intra-industry spinoffs (Klepper, 2009).

Yet, most of the prior literature simply acknowledges differences in employee learning and has little to say about how this knowledge is acquired and differs due to the organisation of labour inside firms. In this paper, I introduce a new theory on spinoffs that unravels this question and allows understanding the knowledge flows from incumbents to spinoffs. Most closely related to this paper Hvide (2009) builds a model on spinoff formation with an emphasis on the size of firm that entrepreneurs were previously working for. Small and large firms, he argues, differ in their capacity to acquire information about the quality of the idea, being large organisations worse at monitoring and therefore, knowing the precise value of ideas. Here, however, I focus on the composition of human capital that would-be entrepreneurs acquire in small and large firms and investigate how this affects their decision to spin-out and the quality of the new firms.

Since knowledge is often tacit and hardly codifiable great part of the organisational knowledge is embodied in workers and transferred as workers move (Cowan et al., 2000; Agrawal et al., 2006). I consider task-specific human capital[1] as the measure of skills that are accumulated

[1]There is a growing literature also taking the task-based approach. However, task-specific human capital is mainly discussed in the context of internal promotions (Gibbons and Waldman, 2003, 2004), occupational mobility and wage growth (Gathmann and Schönberg, 2010) and job design (Borghans and Ter Weel, 2006; Garicano, 2000; Garicano and Wu, 2010). To the best of my knowledge none previous work has adopted this theory to explain entrepreneurial entry. My approach also differs from many of these works in the sense that individuals here do not make actual human capital investment decisions until the start of the second stage. It is assumed that workers are

in the workplace and portable across occupations (Gibbons and Waldman, 2004; Gathmann and Schönberg, 2010). As opposed to specific human capital, task specific human capital is valuable in all jobs that involve carrying out the same task, regardless it is in the same firm or not. Workers learn by doing and as a result of the job design. I argue that given the limited division of labour in smaller firms (Becker and Murphy, 1992), employees in these organisations acquire more balanced skills, contrary to workers in large firms who concentrate in the skill they better perform. This implies that entrepreneurs emerging from small firms transfer knowledge from more diverse aspects of the business and create spinoffs more related to the main activity of the incumbent firm. In this model, workers in large firms benefit from higher returns to human capital which increase their opportunity costs to switch to an occupation that requires a different combination of skills. Since becoming an entrepreneur implies performing multiple tasks and makes part of their specialised skill unutilised, the minimum quality of the business idea at which workers are willing to reveal their discovery is higher and, therefore, entrepreneurs emerging from large firms will be of highest quality.

I report findings related to the transition into entrepreneurship and their quality. To do so, I use a new dataset of individual entrepreneurs in the UK that provides retrospective information about their previous job. I find weak evidence that most entrepreneurs come from small firms, although the magnitude and significance of this association increase substantially when considering entry in the same industry as their parent firm operates. I conclude that this finding supports my prediction of workers in small firms acquiring diverse skills and knowledge on-the-job and applying them in the new firm. This enriches the so-called "small firm" effect concept, that is the fact that small firms are the source of the vast majority of entrepreneurs, but I recognise that my work differs from some others in that I look beyond the determinants of self-employment by including all new firm founders. When examining the quality of spinoffs, I find a strong association between firm size and expected growth of the firm, which is consistent with the prediction that the best ideas are implement by employees coming from bigger firms. This is of particular interest, as it suggests that although balanced skills acquired in small firms

exogenously assigned to firms, so they cannot freely choose how much to invest in each skill neither the breadth of their knowledge during the first period. These are given by the size of the firm and the fixed available time, which limits the depth of the knowledge they can accumulate in certain skills.

enhance the likelihood of switching to entrepreneurship this is not a sufficient condition to succeed as an entrepreneur. And without ruling out the valuable role of small firms promoting this transition, I speculate that specialised human capital could be equally or even more valuable to set up growth oriented businesses.

An important feature of the dataset is that it contains information about the entire adult population and allows targeting not just self-employees but all entrepreneurs, including those with and without employees, that are currently setting up a business. This differs from more restricted definitions that have been used so far. Some studies have used longitudinal labour data on the matching of employees and employers, usually from Denmark, Norway or Portugal (Dahl and Reichstein, 2007; Eriksson and Moritz Kuhn, 2006; Sorensen, 2007; Moen, 2005; Nanda and Sorensen, 2010), or on a sample of qualified scientists and MBAs (Elfenbein et al., 2010; Dobrev and Barnett, 2005), and others have relied on data from industry market research reports (Agarwal et al., 2004; Christensen, 1993; Sapienza et al., 2004). They often also differ in the criteria to define spinoffs, in particular in self constructed datasets, which makes them many times difficult to compare. For instance, Gompers et al. (2005) consider initial executive officers as founders of the new venture and all previous affiliations as spawner firms, while for Dahl and Reichstein (2007) spinoffs are created by two or more employees that quit the same firm prior starting the new venture in the same industry. The present dataset does not, however, require making assumptions over the linkages between spinoffs and spawning firms and broadens the scope of the analysis to all industries and adult population. In addition, it covers a wide range of individual and firm level characteristics that enriches the analysis and are not usually contained in career history datasets.

This paper mainly contributes to the literature on spinoff formation and secondly, as mentioned, it relates to the strand that examines on-the-job learning and task-specific human capital acquisition in particular. Despite the rapidly growing number of studies on spinoffs, the literature is still vague about what underlies the employee learning and it rarely forms the core of the papers. Two recent exceptions that capture theoretically learning mechanisms are Franco and Filson (2006) and Klepper and Sleeper (2005). The former model a setting where employees can imitate the knowledge of their employer and create their own venture, or rather remain within the firm to improve their know-how. In contrast, employers can only innovate by hiring researchers and are incapable of imitating. Then, as the industry evolves the distribution of know-how increases and the necessary knowledge that the researcher requires to quit and succeed as an entrepreneur also rises. In equilibrium employers anticipate the possibility that workers will imitate their technology in the future, so they offer a lower wage. The difference between the outside salary, i.e. the one that the researcher could obtain in another industry, and that paid by the firm is higher the greater the know-how of the firm. This result is somehow similar to the one obtained by Pakes and Nitzan (1983), and supported empirically in Moen (2005), though in these cases employers offer a lower salary in the beginning but an additional performance contingent bond in subsequent periods, while in Franco and Filson (2006) researchers need to create a spinoff in order to capitalise their knowledge. Using data from the rigid disk drive industry they confirm that firms with higher know-how spawn more ventures.

Klepper and Sleeper (2005) develop a Hotelling type model where the price of all products is the same, so consumers buy the one that is closest to their preferences. Firms' R&D investments and marketing know-how generate new variants of the existing product, which are produced at a lower cost than the first version due to the accumulated knowledge that is accessible to just employees and the firm. Thus, spinoffs and the firm have cost advantages over independent start-ups as a result of the underlying learning process. The model has several implications that are tested using laser industry data. First, spinoffs have a smaller market share than other types of entrants, which suggests that they enter in "niche" markets. Even if they offer a product similar to that of their parent firm, spinoffs need to differentiate to succeed in the market. Favourable demand conditions do not have any effect on the spinoff rate of entry as they do on other entrants, as far as the expected minimum demand is met, but adverse conditions will definitely deter their entry. The empirical analysis confirms that better performing firms spawn more firms, but there is no evidence on the learning effect of employees from their parents' technology as found in Franco and Filson (2006). As pointed out by Klepper (2001) "(...) the quality of a parent's experience conditions what employees learn, but exactly how this occurs is a black box in the learning theories" (p.665). None of these papers, however, analyses the process of workers' knowledge acquisition nor the impact of the size of the firm, which are at the core of this paper.

On the empirical side, a number of papers have tangentially accounted for the employee learning mechanism promoting spinoff activity. Burton et al. (2002) and Agarwal et al. (2004) highlight not just informational but also reputational advantages that "prominent" firms, firms with high visibility and abundant knowledge, offer employees in the course of their work. In other words, these working environments predispose employees to recognise entrepreneurial opportunities by enhancing their ability to interpret and manage cutting-edge knowledge and exposing them to experiences and co-workers that have succeeded in the setting up of their business. Moreover, previous institutional affiliation helps entrepreneurs accessing to external financing, as it reduces the information asymmetry between entrepreneurs and external investors about the quality of the venture. As Klepper (2001) posits as well that employees have greater learning opportunities in non-mature technologies, so when combined with a greater density of small firms in the industry higher spawning activity will occur. Finally, Garvin (1983) asserts that the technology needs to be embodied in skilled human capital in order to be easily transferable from one firm to another. My point is different, since I focus on the learning differences that arise due to different degrees in the division of labour, rather than additional benefits that could result from working in certain working environments and industries.

As said, this paper is highly related to this increasing empirical evidence on the origin of entrepreneurs in respect to its emphasis on entrepreneurs' previous firm size. Many studies assert that most entrepreneurs create their firm after quitting a job in a small firm (Parker, 2009; Wagner, 2004; Sorensen, 2007; Elfenbein et al., 2010; Hyytinen and Maliranta, 2008; Hvide, 2009; Gompers et al., 2005). One major issue in these studies, as it is in the present, is to disentangle contextual effects from the sorting of employees with different attitudes and abilities into small firms in the first place. Sorensen (2007) finds evidence for bureaucratic work environments detrimenting entrepreneurial behaviour and learning opportunities for employees, since they prevent the development of entrepreneurial skills, limit their exposure to opportunities and increase the opportunity costs of quitting the firm by offering stability and promotion incentives. Cooper (1985) summarises the benefits of working within a small firm as the exposure to technologies and broader experiences, including the management of small firms. In contrast, Parker (2009) finds stronger support on the self-selection of less risk-averse individuals into small business employment and Elfenbein et al. (2010) emphasise in both enhancing learning opportunities in small firms as well as the sorting of individuals with stronger preferences for independence and autonomy and lowest and highest skills into small firms. My approach is novel in formalising the human capital accumulation in small and large firms and advances this line of work by studying together linkages between the acquisition of human capital and the performance of the newly created firms.

The reminder of the paper proceeds as follows. Section 2 lays out a stylised model that generates a set of predicitons on the relationship between entrepreneurial entry and human capital formation, as well as the quality of the ideas implemented in spinoffs. Section 3 introduces the data and provides the results of the empirical analysis. Finally section 4 concludes.

2 A Basic Model

I build a simple model of spinoff formation along the lines of Hvide (2009). Assume that each individual works for 2 periods. In the beginning of period 1 each individual is randomly assigned to a firm and work there for the first period, where he acquires task-specific skills that add to his innate human capital. At the end of the first period the employee discovers a business idea with quality x. We could think, for example, the business idea to be a new product, technology or new marketing approach. X follows a cumulative distribution function $F(x)$ with density function $f(x)$ on the support $[0, 1]$ and is increasing in x. At this point the employer offers a new labour contract to the employee, who will face the choice of accepting it or rather quitting the firm and exploiting the idea in his own. In period 2, the worker, or alternatively the entrepreneur, obtains the returns in the form of a wage or profits. In the initial setting I consider that the information is complete, i.e. both employee and principal observe x. In the following section, discoveries and valuations are privately observed by the worker, who faces the choice of signaling the discovery of the idea and negotiating an ex-post contract or rather keeping it in secret and earning a continuation wage.

I start by describing the human capital formation. Let k_i the skills to perform task i and $t_i \in [0, 1]$ the time allocated to perform the task, each worker being endowed with a unit of time in each period. Different occupations entail a different combination of task-specific skills and these are acquired on-the-job without any firm- or employee-specific investments, being effort differences negligible, and fully depend on the time spent accomplishing the task. Suppose that the production process consists of T tasks and these are complements, meaning that they all need to be performed to produce output. Tasks are not ranked in terms of their difficulty and as in Becker and Murphy (1992) each worker in the firm is assigned a subset of tasks of the same size: $s = T/n$ where the numerator n denotes the number of employees in the firm. Workers split their unit of time equally between the tasks, thus the time they spend in each task is the inverse of the span of tasks ($t_i = 1/s = n/T$). That is, the degree of specialisation is defined by the width of the span of tasks and it is directly related to the size of the firm. This implies that workers in small firms become generalists, or "jack of all trades", and develop multiple skills; workers in large organisations instead invest in fewer skills. If we think of both extreme cases, generalists perform all tasks and spend $1/T$ of the time in each task, while specialists employ the whole unit of time to perform a single task. In the particular case in which the number of employees is greater than the total number of tasks, $n > T$, I consider that multiple workers are assigned to the same task and become behave like specialists.

A justification for this key result lies in the theory of horizontal division of labour and on-the-job learning. The idea about division of labour shaping the human capital of workers is first argued by Smith (2000):

> "The difference of natural talents in different men, is, in reality, much less than we are aware of; and the very different genius which appears to distinguish men of different professions, when grown up to maturity, is not upon many occasions so much the cause, as the effect of the division of labour. The difference between the most dissimilar characters, between a philosopher and a common street porter, for example, seems to arise not so much from nature, as from habit, custom, and education." (Book 1, op. 28 cp. 15)

His discussion about the increased specialisation of the labour force in pin factories serves to illustrate his claim over the productivity gains that can be achieved through the division of labour. His assertion that "the division of labour is limited by the extent of market" focuses on the size of the market as the main constraint to specialisation and advocates the trade across countries as the means to expand markets and allow workers performing fewer tasks. It is not until Demsetz (1988) and Becker and Murphy (1992) when this discussion turns to the firm level context[2]. Becker and Murphy (1992) argue that there are other team size determinants beyond the extent of the market, say the costs associated with coordinating workers with different specialties and the expansion of knowledge, as it is also pointed out by Demsetz (1988). Again, specialisation allows higher productivity since learning new tasks requires costly time. Thus, as firms get larger the set of tasks that has to be carried out is subdivided among more workers, who perform more narrowly defined jobs and consequently acquire greater task-specific knowledge.

Turning back to my model, as said, this translates to consider workers in large organisations as specialists and those in small firms generalists. The allocation of time across tasks depends therefore on the size of the firm: this prevents workers in small firms from investing the available unit of time on the tasks they inherently better perform; conversely, allocating the time in a narrower set of tasks permits workers in large firms learning and using fewer skills more intensely.

Formally, human capital in period t is accumulated as:

$$K_t = \sum_{i=1}^{T}(t_{it}t_{it-1} + t_{it}k_{i0}) \tag{1}$$

where $k_i^0 \in [0, 1]$ are innate skills to perform task i.[3]. Note that during the first period each worker's human capital value is the sum of the weighted innate skills for the tasks he performs ($K_1 = \sum_{i=1}^{T} t_{i1}k_{i0}$). It is in the second period when former job experience adds to the ability to perform the task.

At the end of the first period the worker can quit to form a new business. and get the payoff:

$$xK_2 - c$$

where c denotes the start-up costs that the entrepreneur has to incur. Combining and rear-

[2]This responds to the fact that the degree of specialisation has remained stable or increased moderately in many markets despite markets being expanded enormously since Smith's claims (Borghans and Ter Weel, 2006).

[3]This could also represent the sum of innate skills and the human capital acquired through education before entering the labor market.

ranging with the human capital equation (1), I obtain

$$x\sum_{i=1}^{T} t_{i2}t_{i1} + x\sum_{i=1}^{T} t_{i2}k_{i0} - c \tag{2}$$

As in Gathmann and Schönberg (2010) the first term can be interpreted as the portable skills across occupations and the second term as the quality of the match between worker's innate skills and those required in the chosen occupation. Notice that the time spent in each task shapes on one side the composition of human capital and on the other side, it determines the productivity of the entrepreneur. This feature of the model relates to the idea that the value of an innovation depends on the assets and capabilities to which it is combined (Teece, 1986; Gans and Stern, 2010), in this case represented by the knowledge embedded in the form of human capital rather than the more traditional view of tangible assets. This means that although the idea might be of high quality, it is necessary to combine it with complementary knowledge to increase its profitability.

The key insight here is that the size of the firm constraints the transferability of skills. Taking an example to see this, consider the mentioned extreme case where workers in small firms have balanced skills and spend $1/T$ of their available time in all T tasks and workers in large firms supply their time to a single task. Assume that entrepreneurs are characterised as being generalists (as in Lazear (2005, 2004)) since they need to accomplish many tasks and require breadth of expertise to succeed. That is, they also spend $1/T$ of the time to perform all T tasks. Now think of a worker in small firm switching from paid employment into entrepreneurship. He transfers $(1/T) \times (1/T) = 1/T^2$ of his task-specific skills in each task, which sums ups to $1/T$, and maximises the utilisation of the acquired human capital. In contrast, a worker from a large firm, a specialist, is unable to transfer all the knowledge he acquires if he becomes an entrepreneur. In case he remains in the same occupation after the first period his portable human capital stock would reach $1 \times 1 = 1$, while depreciating to $(1/T) \times 1 = 1/T$ if he has to allocate part of the time to other tasks when being an entrepreneur. This delivers the result that the underutilisation of task-specific human capital is minimised when workers carry out the same set of tasks or alternatively, a subset of this set. As shown, both workers in the example transfer the same total amount of task-specific human capital, but the difference lies in how diverse this knowledge is and the skills that get unutilised after changing the tasks to perform.

Full Information

In this section I describe the full information setting that will serve as a benchmark for the following more realistic case: here both workers and the employer are certain about the quality of the discovered idea. In order to retain the worker within the firm the employer should offer him in the form of a fixed wage, denoted w, at least what he would earn if becoming an entrepreneur. Formally:

$$w \geq x \sum_{i=1}^{T} t_{i2} t_{i1} + x \sum_{i=1}^{T} t_{i2} k_{i0} - c \tag{3}$$

Let α be the cost advantages that the incumbents can benefit if the idea is developed within the firm. The value of the business idea is then αx. I assume that $\alpha > 1$, meaning that the firm achieves synergies, such as sharing existing production facilities, marketing expertise, more favourable funding sources and tax advantages (Bankman and Gilson, 1999). These potential advantages will be determined by the complementarity between the business idea and the core activity of the firm. These will be reduced when the project is more afield from the core expertise of the firm or conversely, too close so that it cannibalises its existing market share.

Together with the minimum wage that satisfies the participation constraint of the worker (3), it yields a positive payoff to the employer $\alpha x - w = \alpha x - x \sum_{i=1}^{T} t_{i2} t_{i1} - x \sum_{i=1}^{T} t_{i2} k_{i0} + c > 0$[4] and shows that all ideas will be developed by incumbents and no spinoff will be formed.

Asymmetric Information

Under the asymmetric information setting the worker observes x but the employer does not, instead the latter just knows its distribution, $f(x)$.[5] Following the approach by Hvide (2009)

[4] Hvide (2009) shows that under the condition $c < 0$, employees will leave and create their own firm, despite this outcome not being optimal. This would occur when c consists of start-up costs as well as non-pecuniary benefits of independence (Blanchflower and Oswald, 1998; Hamilton, 2000), being the latter greater. For simplicity, this option is ignored here.

[5] In Hvide (2009) employers in large and small firms differ in the quality of information over x they can access: while managers in small firms can directly observe the true value x, managers in large firms just know its distribution. Here, I do not make assumptions about the completeness of information based on the size of the firm, but consider that both small and large firms suffer from incomplete information.

the employer's problem is to maximise the expected profits subject to workers' participation constraint (3), which rearranging gives $z = \frac{w+c}{\sum_{i=1}^{T}(t_{i2}t_{i1}+t_{i2}k_{i0})}$. This gives:

$$\max_{z} \int_0^z (\alpha x - w)f(x)dx = \int_0^z (\alpha x - z\sum_{i=1}^{T} t_{i2}t_{i1} - z\sum_{i=1}^{T} t_{i2}k_{i0} + c)f(x)dx \tag{4}$$

And the first order condition requires

$$\Pi_z^{'} = (\alpha z - z\sum_{i=1}^{T} t_{i2}t_{i1} - z\sum_{i=1}^{T} t_{i2}k_{i0} + c)f(z) - (\sum_{i=1}^{T} t_{i2}t_{i1} + \sum_{i=1}^{T} t_{i2}k_{i0})F(z) = 0$$

Whenever the set of tasks in the first period is a subset or the same set of tasks in the second period the worker makes use of all the task-specific knowledge, then $\sum t_{i2}t_{i1} = t_{i2}$. It is intuitive to assume that entrepreneurs are assigned an equal or a wider set of tasks than when they were employees, given the limited division of labour in start-ups. Thus workers will perform at least the same span of tasks, and the set of tasks in the first period will be contained in the set of the second period to avoid task-specific human capital getting unused. The above expression simplifies to

$$\Pi_z^{'} = (\alpha z - zt_{i2} - z\sum_{i=1}^{T} t_{i2}k_{i0} + c)f(z) - (t_{i2} + \sum_{i=1}^{T} t_{i2}k_{i0})F(z) = 0$$

Hence it will not be optimal for the employer to keep all employees in the firm (notice that $\Pi^{'}(1) = -(t_{i2} + \sum t_{i2}k_{i0}) < 0$). In contrast to the full information setting, the employer here cannot pay the worker based on the actual value of the idea and retaining workers with better ideas implies offering higher wages to all workers. Thus, ideas of quality above the optimal level z^*(i.e. $z \,\epsilon\, [z^*, 1]$) will be developed in spinoffs.

Another important result is that the size of the firm has no effect in the optimal quality level $z^*(\frac{\partial z^*}{\partial n_1} = 0)$, so neither in the quantity of spinoffs nor their quality. This is because the total transferred value of the task-specific human capital is independent of the firm size, therefore workers from small and large firms transfer the same total value of human capital making no difference in their incentives to spin out. To say it in another way, the size of the firm only determines the composition not the value of the task-specific human capital that is portable and transferring more diverse knowledge from small firms to start-ups does not add extra value to the idea.

The model also captures that z^* decreases with the size of the entrepreneurial team denoted n_2. Implicitly differentiating the first order condition and applying the chain rule with respect to the entrepreneurial team size it satisfies:

$$\frac{\partial z^*}{\partial n_2} = \frac{\partial z^*}{\partial t_2}\frac{\partial t_2}{\partial n_2} = \frac{z^* f(z^*)(\sum k_{i0}+1) + F(z^*)(\sum k_{i0}+1)}{\partial^2 \Pi / \partial z^2}\frac{1}{T} < 0$$

When we allow entrepreneurs to form teams and make use of their specialised knowledge more intensely, the entrepreneurial option becomes more attractive irrespective the firm size the individual is originally working for. It also improves the quality of the match for employees that are not innately so well versed for all tasks since they can let other founders to perform them. As a result, the rate of spinoff creation rises and the average quality of spinoff decreases[6].

In the above analyses, I have illustrated that the firm size does not affect the rate of spinoff formation. So far, I have assumed that the employer observes directly x or $f(x)$ and defines the wage conditional on being at least as high as the entrepreneurial option. In the asymmetric information framework, this implies that the worker is better off by signaling the discovery of x and forcing the employer to make a new wage offer to avoid his departure. Potentially, however, it could be optimal for workers not to reveal any information and to demand a continuation wage in period 2. Thus I investigate the effect of firm size on the quality level at which the worker will be indifferent between staying in the firm and setting up his own firm and allowing for the fact that continuation wages update in terms of the accumulated human capital. Letting the return to human capital to be equal across skills ($w_1 = w_2 =, ..., = w_T$), wages in the second period are given by

$$w_2 = wK_2 = w\sum_{i=1}^{T} t_{i1}t_{i1} + w\sum_{i=1}^{T} t_{i1}k_{i0} \tag{5}$$

[6]It also yields some interesting expressions already shown in Hvide (2009) when differentiating over c and α. A rise in start-up costs (c) decreases the rate of spinoff creation (formally, $\partial z^*/\partial c > 0$), since it reduces the expected net value of the idea for potential entrepreneurs and means that providing the minimum wage to keep employees within the firm is cheaper for the employer. Also since $\partial z^*/\partial \alpha > 0$ the employer will have greater interest in developing the ideas within the firm the higher the synergies and complementary assets that are exclusive to it.

and workers signal the discovery of the idea if and only if

$$x'(\sum_{i=1}^{T} t_{i2}t_{i1} + \sum_{i=1}^{T} t_{i2}k_{i0}) - c \geq w(\sum_{i=1}^{T} t_{i1}t_{i1} + \sum_{i=1}^{T} t_{i1}k_{i0})$$

As before, the minimum value of the idea for the marginal worker is then

$$x' \geq \frac{w(\sum t_{i1}t_{i1} + \sum t_{i1}k_{i0}) + c}{\sum t_{i2}t_{i1} + \sum t_{i2}k_{i0}} = \frac{w(t_{i1} + \sum t_{i1}k_{i0}) + c}{t_{i2} + \sum t_{i2}k_{i0}} \tag{6}$$

and the derivative with respect to the firm size yields

$$\frac{\partial x'}{\partial n_1} = \frac{\partial z^*}{\partial t_1}\frac{\partial t_1}{\partial n_1} = \frac{w(1 + \sum k_{i0}) + c}{t_{i2} + \sum t_{i2}k_{i0}}\frac{1}{T} > 0$$

This reflects the higher opportunity costs that workers from large firms face relative to workers in small companies. This result is due to a greater division of labour and more specialised knowledge in large firms, which allows workers to increase the use of the acquired task-specific skills and become more productive. Hence they benefit from higher wages and demand higher returns to switch to an occupation that makes part of their task-specific human capital unused.

Figure 1 shows the three possible outcomes on a line that represents the the quality of the idea x. Workers with ideas above quality x' will reveal a signal to their employer and make the decision on whether to accept the new labour contract or rather to leave and set up their own venture. All other workers will demand the continuation wage. Workers with ideas between x' and z^*will stay in the firm and will earn z^*, and those with ideas above this threshold will leave to develop the idea via spinoff. Notice that this will occur as long as $x' < z^*$, otherwise workers will not reveal the discovery to their employer and all ideas generated within incumbents will be implemented in spinoffs. More precisely, only workers for whom the entrepreneurial payoff exceeds x' will become entrepreneurs. Because x' is positively correlated with the size of the firm, while z^* being independent, this is more likely to occur the higher the size of the firm (as well as higher start-up costs and wages per labour unit). This means that the number of spinoffs emerging from large firms will be smaller but on average of a better quality.

Discussion and Empirical Predictions

The above framework produces novel predictions regarding the formation of spinoffs, the relationship between the transferred knowledge and the main activity of the incumbent firm and finally, the quality of the ideas implemented in spinoffs. First, it reveals that workers from small and large firms differ in the composition of human capital they can transfer if transitioning into entrepreneurship. More precisely, workers from small companies are able to bring all the task-specific skills they acquire in their previous employment, in contrast, highly specialised human capital of workers in large firms is just partly portable. This is due to the loss of task-specific skills that workers incur when moving to occupations with different skill requirements. It is interesting to note that workers from small companies transfer more diverse skills; despite lacking the deeper knowledge that characterise workers in large firms, working in small firms enhances learning opportunities to understand and acquire expertise of broader aspects of the business. This suggests that workers from small companies undertake projects that are closer to the core business of their former employer particularly if skills are specific to the industry, or in other words, task-specific human capital is similar to the industry-specific human capital (Gibbons and Waldman, 2004).

An alternative argument suggests that individuals innately endowed with more balanced skills, that is, being equally good or bad in all of them, self-select into small firms, invest in more balanced set of skills and are then more likely to become entrepreneurs. Remember that there are two rationales for wage growth in this model: it could be the result of human capital aquisition and second, the improvement of the match between innate skills and job requirements. This logic would imply, therefore, that individuals versed innately with balanced skills can achieve higher wages in small firms in the first period because of a better matching or alternatively, they can transfer greater task-specific human capital to the spinoff. However, individuals will always have incentives to specialise in their best skill (if any) particularly, the higher the distance between the weakest and strongest skills[7]. It is true that they will have a comparative advantage in

[7] Other papers that set up similar models to assess human capital investment decisions, such as Rosen (1983), Lazear (2005) and Garicano and Wu (2010) incorporate learning costs that are independent of the rate of utilisation of the skills and create the incentives to invest in a more limited set of skills and use them more often. Here, learning is assumed to be costless but the incentives come from the fact individuals can just invest a limited amount of time in learning. Given that individuals are endowed with an innate or after schooling stock of human

occupations that require the use of a variety of skills but this does not improve their subsequent performance as entrepreneurs since the total portable value of human capital is independent of the firm size. Thus the ability sorting story (Elfenbein et al., 2010; Sorensen, 2007; Parker, 2009; Wagner, 2004) does not seem to drive the decision to spinoff here. I will return to this issue in the empirical section.

Second, it shows that employers are unable to retain all workers within the firm, but just employees with ideas on the top range of the quality distribution will leave the firm. Similarly, and consistent with previous studies, spinoffs develop projects that are less attractive to the parent firm (i.e. with lower α in this case) (Hvide, 2009; Hellmann, 2007; Subramanian, 2005; Gompers et al., 2005; Klepper, 2009; Pakes and Nitzan, 1983) and require lower start-up costs (Aghion and Tirole, 1994; Anton and Yao, 1995).

The theory also provides support to the opportunity cost argument based on the fact that workers in large organisations earn higher wages relative to small firms, thus the expected return of the idea at which workers in these organisations are willing to reveal their discovery or quit the firm is higher. Hence, large firms may generate less spinoffs but these will be of highest quality and will on average outperform spinoffs coming from small firms. The model predicts that when the continuation wage in the second period is higher than what the worker could make as an entrepreneur no revelation of the discovery is made to the employer. Incumbents may consequently miss valuable business ideas as a result of promoting skill premiums through a greater specialisation of labour as the means to increase productivity.

3 Empirical Analysis

3.1 Data

I analyse data comprising a representative sample of the adult population aged 18-64 in the UK. The survey is part of the Global Entrepreneurship Monitor (GEM) project that aims to measure and understand entrepreneurial activities at national level, as well as serve to make cross-country comparisons. Data is collected through a random telephone survey on an annual basis, but I use

capital that determines their initial productivity in each of the tasks, it always pays to work in a job that is more intense in this task.

data from the 2010 wave, when an extension to the standard questionnaire was made to record the previous employment of entrepreneurs and additional questions to those of currently being in paid employment. The database includes information on 10,403 individuals.

I follow the definition of entrepreneurs established in the GEM project identifying individuals who are currently actively involved in setting up a business they will own or co-own[8]. In practise, this accounts for businesses that have not paid salaries for more than 42 months, so I exclude owner-managers of businesses above this threshold in order to avoid any survival bias. The overall rate of entrepreneurship in the adult population is 5.05 percent, although for the purpose of this study I restrict my attention to the adult population being currently or recently employed by others. This results in 5,895 individuals reporting to be in part- of full-time employment or have been so at any time in the last two years and working for someone else in the job. Similarly, out of the 525 entrepreneurs in the sample 415 were previously or are still in paid employment[9]. Therefore, I leave out data of individuals who are currently retired or disabled, in full-time education, unemployed and full-time home-makers, and have been so in the last two years. Unfortunately, due to missing values the sample gets notably reduced in the empirical analysis.

Table 1 provides the mean and standard deviation of the set of relevant variables for entrepreneurs and employees separately. The group mean differences between employees and entrepreneurs suggest that the latter have worked on average in smaller firms, more likely in the private sector and are predominantly men. Interestingly, they are remarkably more likely to be grown in families where their parents ever ran a business, which is consistent with previous empirical studies (Blanchflower and Oswald, 1998; Dunn and Holtz-Eakin, 2000; Kawaguchi, 2003; Halaby, 2003) and confirms the importance of values and norms learned in early stages of life. I do not find significant mean differences, however, on the educational attainment and age.

[8]For a more detailed description of the methodology see Reynolds et al. (2005) and appendix B.

[9]Precisely, 25 percent of entrepreneurs are still in part- or full-time employment in parallel with creating their own business. This confirms the potential under-representation of entrepreneurs in datasets coding solely the main occupation of individuals in the labour force as many people may enter and exit entrepreneurship while keeping another salaried job.

3.2 Analysis

Transition into Entrepreneurship

I first analyse the probability of transitioning into entrepreneurship given the size of the last employer, measured by the number of employees, and mentioned set of control variables: whether the business operates in the private sector, industry dummies, the age and gender of the respondent, whether the he earned a university degree and his parents ever ran a business (see the appendix A for a more detailed description of the variables). For most models I compare the continuous and categorical forms of the business size. Given that the data on firm size is highly skewed, I follow the winsor technique and truncate the values at the 99% percentile and I also use the logarithmic form. For the categorical case I construct five dummies with cut-off points at 10, 20, 50 and 250 employees[10].

Table 2 presents the results of the logistic regression where the unit value of the dependent variable represents becoming an entrepreneur. The two columns take the whole sample of employees and entrepreneurs. The results indicate just a negative but statistically insignificant effect of firm size on transitioning into entrepreneurship. They show that being grown in a family with entrepreneurial parents exerts an important positive impact in the start-up decision (an increase of 0.02 in the predicted probability of 3.24 percent of becoming an entrepreneur).

I then explore the likelihood of creating a firm in the same industry as the former employer operates (or current employer for entrepreneurs still in employment), referred as intra-industry spinoff in the literature (Klepper, 2009). I create a new variable measuring the degree of relatedness between the two industries by looking at the International Standard Industrial Classification (ISIC) four-digit codes provided in the dataset[11]. I define intra-industry spinoffs as new businesses whose ISIC three-digit code match with the parent firm's code. I also explored alternatives procedures to define intra-industry spinoffs: using the answer entrepreneurs provided to the question on whether they entered the same industry or not, the four-digit match of industry codes and a weaker condition with two-digit codes. I chose the three-digit ISIC codes to minimise the subjective response error and to avoid using a too restrictive condition, while still capturing

[10] I also explored seven and three size categories, which produced similar results.

[11] Respondents were not asked about the specific ISIC code but the kind of activity his employer engages in or the way it would be listed in a business directory.

enough proximity of industries. The results are shown in table 3. They support (columns 1 and 2) the claim that as firms get smaller entrepreneurs are more likely to enter the same industry they were working before, presumably as a result of having more diverse transferable skills. That is, if entrepreneurs transfer different set of task-specific skills, such as technical, commercial, or managerial skills, we could think of workers from smaller firms to benefit from acquiring a more general and complete understanding of their parent firm's expertise. This would consequently make them more likely to discover opportunities in the same sector. This result is robust when I replicate the regression on the subsample of entrepreneurs as shown in columns 5 and 6, which account for the likelihood of entering the same industry conditional of being an entrepreneur. Saying in another way, decreasing the previous employer's business size by one percent is associated with a 3.6 percent increase of the predicted probably of entering the same industry (22.3 percent) conditional on becoming an entrepreneur.

Because the decision of entering the same industry can be largely affected by the degree of competition in the industry where the employer operates I investigate this issue by including an indicator for market competition. I construct a Lerner index using information from Orbis dataset (maintained by Bureau van Dijk, 2011). I calculate the average ratio of the operating income after depreciation and amortisation to the net sales across firms (i) in two-digit NACE industries[12] (j) and subtract it from one (Aghion et al. 2005, p. 704-5):

$$C_{ij} = 1 - \frac{1}{N_{ij}} \sum_{i \epsilon j} \frac{profits_{it}}{sales_{it}}$$

I repeat the same procedure for the six years period 2005-2010 in order to correct for any year specific impact and take the average of the measure per industry. The value one of the index reflects perfect competition and values below the unity suggest some degree of market power by existing players. It can be also interpreted as the degree of maturity of the market, as mature and declining markets will have lower profit margins and therefore, values closer to one. This index has been extensively used to measure the degree of product market competition (Aghion

[12]The first and second levels of NACE Rev.2 and ISIC Rev.4 are identical so I could directly merge the categories from the GEM dataset with data from Orbis (http://circa.europa.eu/irc/dsis/nacecpacon/info/data/en/NACE%20Rev.%202%20Introductory%20guidelines%20-%20EN.pdf).

et al., 2005; Bloom et al., 2010) since it provides advantages over other measures of competition. For instance, the Herfindahl concentration index would capture the magnitude of barriers to entry and required sunk costs that new entrants would have to face. The main shortcoming of this measure, however, is that it cannot account for the competition exerted by international companies exporting to the UK. Similarly, data on imports and exports was not available for all industries, so I was unable to use any measure of import penetration to assess the degree of competition (Bloom et al., 2010).

The inclusion of competition measures just marginally alters the significance and the magnitude of the employer's business size effect (columns 3 and 7). As expected, entrepreneurs are more likely to enter the same industry the lower the competition in the industry their employer operates (being statistically insignificant when I condition on becoming an entrepreneur, column 7). Once again, when augmenting the model with the interaction between the measure for competition and (log of) business size (columns 4 and 8) the estimation of the direct effect of business size is almost unaffected. I find that the business size is strongly and negatively associated to the formation of intra-industry spinoffs unless the employer operates in an industry with higher degree of competition. That is, overall employees leaving smaller firms are more likely to enter the same industry, but in markets with greatest competition this effect is reversed and larger firms seem to spawn more spinoffs in the same industry. Although the fact that greater competition makes employees from larger firms to enter a direct competition with their employer could at first glance appear contraintuitive, there are at least two plausible explanations for this: first, it could reflect that larger firms exert lower market power in the industry and leave room for smaller players to compete; and second, it could be the result of markets reaching a maturity stage and requiring specialised knowledge and better ideas to succeed in the industry. I further assess this issue later in this section.

I also consider a plausible alternative explanation to my findings. Given that the survey was conducted while the impact of the 2008 economic crisis was still contracting employment, one could argue that jobs in SMEs have been more severely affected and more employees from SMEs have been forced to find alternatives jobs, along with creating their own business. If this was true we would expect most entrepreneurs coming from small firms, regardless the industry they enter. The estimates have indicated, however, that the effect of employer size is insignificant in this general transition to entrepreneurship (table 2). To further dispel this concern, I look at the proportion of entrepreneurs that affirm creating the new venture to take advantage of a business opportunity as opposed to those who report not to have better choices for work or a combination of both reasons. While being aware of the potential noise in this subjective question, I do not find a positive correlation between opportunity seeking entrepreneurship and previous employer's size, indeed the correlation is negative and insignificant.

Quality of Ideas

The theory predicts that the best ideas come from large companies, due to higher opportunity costs associated with the returns to specialisation. Given that entrepreneurs are being asked when they are still in the process of setting up the business or in the initial months of activity, I lack data on the actual performance of the businesses. However, the database provides information about the number of employees that entrepreneurs expect to hire in 5 years time. Despite acknowledging the lack of precision of this variable, it seems reasonable to consider this measurement error to be random and uncorrelated with the size of the business and a valid proxy to this purpose. I correct again for the skewed distribution of the variable by taking logarithms and compare the OLS regression with quantile regression techniques to better understand the underlying mechanisms in the entire distribution. This permits to see, for instance, the effect of previous employer's size on average expected grow of firms, but more interestingly, in the size distribution of firms and those with highest growth potential.

Table 4 reports the quantile regression estimates for the quartiles q=.25, .50 and .75. As before, columns 1 and 3 use categorical dummies for firm size, while column 2 and 4 the continuous format. The last two models, moreover, control for industries. In addition to the regressors employed in previous models, I include a dummy referring to whether any new intellectual property (trade mark, copyright or patent) has been applied for as a result of the new business. The effect of firm size is statically insignificant until the upper quartile (q=.75), where a percentage point increase in the firm size increases the expected number of employees in 16.5 percent when the rest of variables are taken at their mean. Looking more carefully at the right tail of the distribution different specifications of the quantile regression model, whether including bootsrapped standard error or considering the discrete dependent variable, confirm this effect as it is shown in table 5. Both in this table and figure 2 I compare the quantile regression estimates with the OLS coefficient. The former shows a positive coefficient of firm size over most of the range of the distribution and reflects a larger effect than the OLS estimate (indicated with the horizontal dotted line) over around q=.4. In fact, the quantile estimate increases sharply in the top of the distribution, meaning that the effect of firm size is higher at higher points of the conditional expected growth distribution. The positive correlation between previous employer's size and expected growth is robust to controlling for the degree of competition, number of initial employees and number of founders, which reassures the robustness of the model. As a whole, these estimates provide support for the theoretical prediction that the best ideas are implemented by workers coming for bigger firms.

Identification Concerns

So far I have implicitly assumed no endogeneity problem in the assignment of workers into small and large firms, which allows comparing individuals from both groups without major concerns. The central empirical challenge however lies in distinguishing selection from the "treatment effects" (working in a given firm size being the "treatment" in this case). Although the empirical tests have been conducted on a representative cross sectional sample of the adult population, I am unable to control for unobservable individual characteristics that may non-randomly assign workers into large and small firms. For example, as some authors have pointed out less risk-averse individuals (Parker, 2009) or those with higher preference for certain job values, such as independence and autonomy (Sorensen, 2007; Halaby, 2003) may self-select into smaller firms. Based on the insight of Roy (1951) individuals self-select into occupations with highest expected earnings given their innate skills and the state of the technology in these sectors. Remember that this is formally captured in my model by the second term in brackets in the equation (2), which measures the quality of the match between the innate skills and the required skills in the occupation and has been ignored til now.

I test the sorting argument by exploiting the fact that individuals whose parents were entrepreneurs are potentially more likely to join smaller firms in the first instance. Thus, the effect of previous employer size would get attenuated for this subsample due to sorting (Sorensen and Phillips, 2008). As it has been already shown in table 2 being children of entrepreneurial parents increases significantly the likelihood of switching into entrepreneurship and as expected, the negative effect of employer size gets compensated by this. When including the interaction between employer size and entrepreneurial parents, however, the coefficient of the interaction term turns positive and significant. This rejects the conjecture that the employer size effect is solely due to sorting since we would otherwise observe a negative sign [13]. Indeed, in the rest of the estimations the effect of parents' entrepreneurial experience turns insignificant and does not consistently attenuate the effect of employer's size.

Some previous work has tried to tackle the problem of omitted variable bias by using fixed effects in panel regressions. This allows controlling for unobserved characteristics of individuals, just those which are time invariant, but does not overcome the selection problem that appears to play some role here. To address this issue I use an instrumental variable strategy where the percentage of the employment in large firms (over 250 employees) in i) the county and ii) the region the respondent was born instrument for employer's size. This information is only available for respondent that were born in the UK so those born in other countries are excluded from these estimations. The underlying idea to use these instruments is that individuals born in counties and regions with greater proportion of workers in large firms are also more likely to work in larger organisations irrespective their innate talent and preferences. I use enterprise level data from the UK Business Structure Database that contains information of the universe of businesses registered for Value Added Tax or Pay-As-You-Earn and allows me to aggregate employment information into county level and across different establishment size categories[14]. The independence condition for valid instruments is satisfied as I look at the county of birth of individuals that is, naturally, exogenously assigned. The percentage of employment in large firms has to be also a relevant factor explaining the size of the firm individuals work for. In the 2SLS specification this can be checked by the F statistic of the excluded instruments in the first

[13] Results are available upon request.

[14] I thank Karen Bonner and Mark Hart for providing me this data available at the Virtual Microdata Laboratory, ONS.

stage. Values above 10 are understood to be reliable (Stock et al., 2002) and below this threshold to potentially suffer from weak instruments bias. For the IV identification to work, moreover, there must be enough variation in the fitted values from the first stage which is achieved in this case by using the employment in large organisation at the county level. Because individuals can commute to contingent counties, particularly the closer to the county borders they are, I include the same measure at the regional level as a second instrument.

The results of the transition into entrepreneurship and same industry entry models are reported in table 6. The F statistics are slightly above the border line for strong instruments (10.75 and 11.32, the difference coming from a smaller sample in the second regression), so I re-run the IV models with the limited information maximum likelihood (LIML) estimator that is approximately median-unbiased (Angrist and Pischke, 2009). The results in columns 2 and 6 show that the coefficient estimates remain almost identical and the standard errors are not bigger for LIML, which I conclude as having strong instruments. The effect of previous employer's size is negative for both transitions and as in the logit regressions the coefficient is just significant when estimating the likelihood of individuals creating a spinoff in the same industry. In order to compare the magnitude of the IV estimates with the former results, I show the probit (which would approximately correspond the logit coefficients[15]) and the IV probit estimates in columns 3-4 and 7-8. I find that the effect of the previous employer's size effect is stronger, both in magnitude and significance, when I instrument for this measure and consider the industry they enter. Although the coefficient for the IV specification is also bigger when estimating the likelihood of becoming an entrepreneur, the effect turns statistically insignificant. Thus, these results reaffirm the previous findings on the association between small size employment and same industry entry while lacking substantial evidence for the small firms size effect in the general transition into entrepreneurship.

4 Concluding Remarks

This paper complements others that examine the formation of spinoffs. It provides a new perspective to the discussion by emphasising on the process of learning on-the job, in particular the

[15] Using the logit specification the coefficients are -0.0399 and -0.309 respectively.

set of tasks that workers perform before moving to entrepreneurship. This is argued to shape workers' human capital composition, namely task-specific human capital, and to determine the portable knowledge across occupations. The predictions rest on the assumption that workers in small firms are assigned a more extensive set of tasks and therefore, accumulate balanced skills. Conversely, workers in large firms are able to accumulate human capital on a narrower set of skills and gain proficiency in them. This mechanism provides an explanation to the large proportion of entrepreneurs emerging from small firms and entering the same industry as their former employer operates. I have argued this is due to a more diverse knowledge transferable by workers in small firms.

Beyond the understanding of entrepreneurial origins, the paper incorporates a rationale to understand the source of successful entrepreneurs. Given the ongoing debate on the creation of new jobs, this question inevitably has implications for public policy. I have shown that spinoffs emerging from large companies are the most growth oriented in terms of the expected number of employees in the short term. This result is consistent with a model in which workers in large firms acquire narrower but deeper know-how, thus become more productive, and command higher wages as long as they remain in the same job. If they switch to entrepreneurship part of their task-specific human capital gets unutilised, thus only workers with best ideas leave large firms to create their own business.

One main contribution of this approach is that it uncovers the learning mechanisms that distinguish small and large firms and affect the transition into entrepreneurship. These findings suggest a research agenda that focuses on internal organisational features that potentially affect the set of tasks that workers accomplish. Another direction for future investigation is to extend the theory to a set of complementary tasks and skills and the interaction of workers with different talent within organisations.

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Figure 1: Decision of workers

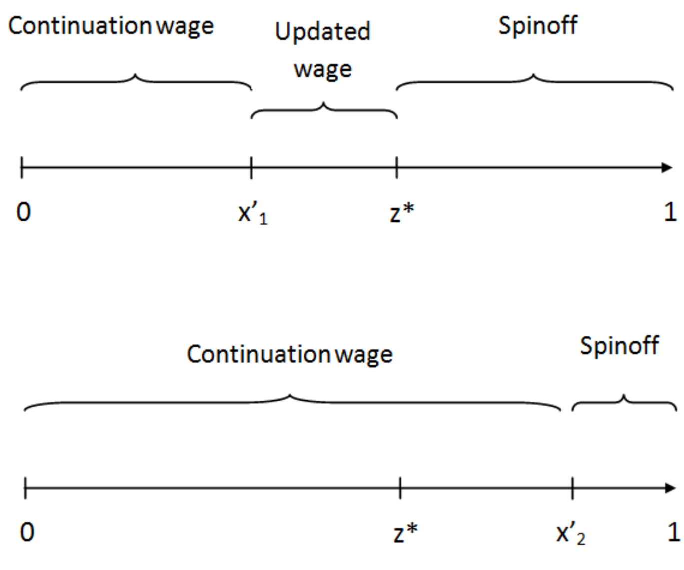


Table 1: Descriptive statistics of employees and entrepreneurs

	Employees		Entrepreneurs		
Log firm size	5.448	(2.967)	4.888	(3.125)	**
Firm size: 1-9	0.132	(0.339)	0.205	(0.405)	**
Firm size: 10-19	0.0776	(0.268)	0.0966	(0.296)	
Firm size: 20-49	0.132	(0.339)	0.159	(0.367)	
Firm size: 50-249	0.207	(0.405)	0.148	(0.356)	*
Firm size: >250	0.451	(0.498)	0.392	(0.490)	+
Private	0.484	(0.500)	0.653	(0.477)	***
Age	42.27	(12.13)	42.79	(11.05)	
Female	0.511	(0.500)	0.330	(0.471)	***
Graduate	0.404	(0.491)	0.443	(0.498)	
Parents run a business	0.265	(0.441)	0.403	(0.492)	***
Observations	4110		176		

Note: Only observations for wich all data for all variables is available are included. Standard deviations in parentheses. Differences in mean. Sig: + 0.10, * 0.05, ** 0.01, *** 0.001.

Table 2: Transition into entrepreneurship: Spinoffs

	(1)	(2)
Log firm size	0.961	
	(0.03)	
Private	1.263	1.279
	(0.25)	(0.25)
Age	1.011^{+}	1.011^{+}
	(0.01)	(0.01)
Female	0.584^{**}	0.596^{**}
	(0.12)	(0.12)
Graduate	1.139	1.146
	(0.21)	(0.21)
Parents run a business	1.762^{**}	1.760^{**}
	(0.32)	(0.32)
Firm size: 1-9		1.325
		(0.33)
Firm size: 10-19		1.204
		(0.38)
Firm size: 20-49		1.037
		(0.29)
Firm size: 50-249		0.862
		(0.21)
Industry dummies	Yes	Yes
Observations	3748	3748
Pseudo R^2	0.056	0.057

Note: Exponentiated coefficients; Robust standard errors in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Transition into entrepreneurship in the same industry: Intra-industry spinoffs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log firm size	0.734**		0.781**	0.727***	0.816+		0.822*	0.762*
	(0.07)		(0.07)	(0.07)	(0.09)		(0.08)	(0.09)
Private	2.573*	2.527*	4.121**	4.196**	2.301	2.456	2.766+	2.956*
	(1.13)	(1.12)	(2.00)	(2.03)	(1.25)	(1.38)	(1.52)	(1.60)
Age	0.998	0.999	0.999	0.999	0.983	0.981	0.986	0.987
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Female	0.592	0.610	0.530+	0.541+	1.076	1.095	0.814	0.802
	(0.24)	(0.25)	(0.20)	(0.20)	(0.54)	(0.59)	(0.39)	(0.38)
Graduate	1.303	1.346	1.320	1.334	1.279	1.440	1.161	1.267
	(0.48)	(0.50)	(0.48)	(0.48)	(0.61)	(0.72)	(0.54)	(0.62)
Parents run a bus.	1.440	1.427	1.359	1.344	1.154	1.120	1.012	0.987
	(0.52)	(0.52)	(0.50)	(0.49)	(0.54)	(0.55)	(0.49)	(0.47)
Firm size: 1-9		7.836***				4.664*		
		(3.96)				(3.46)		
Firm size: 10-19		6.118**				3.636+		
		(3.47)				(2.84)		
Firm size: 20-49		2.859+				4.286*		
		(1.74)				(3.04)		
Firm size: 50-249		1.518				1.012		
		(0.99)				(0.79)		
Competition			0.945+	0.860*			0.952	0.870
			(0.03)	(0.06)			(0.05)	(0.07)
Competition*Size				1.021*				1.017
				(0.01)				(0.01)
Industry dummies	Yes	Yes	No	No	Yes	Yes	No	No
Observations	3457	3457	3090	3090	127	127	120	120
Pseudo R^2	0.124	0.134	0.095	0.101	0.155	0.184	0.120	0.130

Note: Exponentiated coefficients; Robust standard errors in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Expected growth in 5 years. Quantile Regression

	(1)		(2)		(3)		(4)	
q25								
Firm size: 1-9	-0.042	(0.42)			0.32	(0.46)		
Firm size: 10-19	-0.19	(0.56)			0.035	(0.54)		
Firm size: 20-49	0.19	(0.75)			0.013	(0.80)		
Firm size: 50-249	-0.23	(0.52)			-0.17	(0.55)		
Same industry 3 digits	0.27	(0.42)	0.052	(0.38)	0.21	(0.45)	0.020	(0.40)
Log firm size			-0.019	(0.07)			-0.039	(0.06)
q50								
Firm size: 1-9	-0.39	(0.49)			-0.33	(0.51)		
Firm size: 10-19	-0.39	(0.53)			-0.31	(0.52)		
Firm size: 20-49	-0.15	(0.65)			0.059	(0.68)		
Firm size: 50-249	0.12	(0.56)			-0.039	(0.64)		
Same industry 3 digits	0.14	(0.36)	0.16	(0.33)	-0.021	(0.43)	0.066	(0.33)
Log firm size			0.080	(0.08)			0.075	(0.07)
q75								
Firm size: 1-9	-1.40*	(0.56)			-1.21*	(0.53)		
Firm size: 10-19	-1.33^{+}	(0.71)			-1.06	(0.66)		
Firm size: 20-49	-0.82	(0.60)			-0.45	(0.69)		
Firm size: 50-249	-0.68	(0.56)			-0.44	(0.57)		
Same industry 3 digits	-0.028	(0.33)	0.0025	(0.26)	-0.077	(0.39)	0.036	(0.29)
Log firm size			0.16**	(0.05)			0.15**	(0.06)
Observations	102		102		102		102	

Note: Standard errors in parentheses. All regressions control for Private, Age, Female, Graduate, Parents ever run a business and Project involves IP. Columns 3 and 4 also control for industry.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Expected growth in 5 years. Comparison of .75 quantile coefficients

	(1) OLS	(2) QR_75	(3) QRb_75	(4) CQR_75
Log firm size	0.0676	0.165**	0.165*	0.0882*
	(0.05)	(0.06)	(0.07)	(0.04)
Same industry 3 digits	-0.0760	0.0566	0.0566	0.0204
	(0.25)	(0.32)	(0.32)	(0.21)
Private	0.346	0.409	0.409	0.307
	(0.29)	(0.41)	(0.43)	(0.33)
Age	-0.00764	-0.0114	-0.0114	-0.00589
	(0.01)	(0.01)	(0.01)	(0.01)
Female	-0.434*	-0.553+	-0.553+	-0.366+
	(0.21)	(0.31)	(0.31)	(0.21)
Graduate	-0.0860	0.321	0.321	0.199
	(0.24)	(0.36)	(0.36)	(0.23)
Parents run a business	-0.0235	0.0368	0.0368	-0.0793
	(0.24)	(0.34)	(0.35)	(0.21)
Project involves IP	0.810*	0.513	0.513	0.282
	(0.38)	(0.62)	(0.65)	(0.24)
Constant	0.957+	1.163+	1.163+	-0.0259
	(0.50)	(0.65)	(0.69)	(0.47)
Industry dummies	Yes	Yes	Yes	Yes
Observations	100	100	100	100

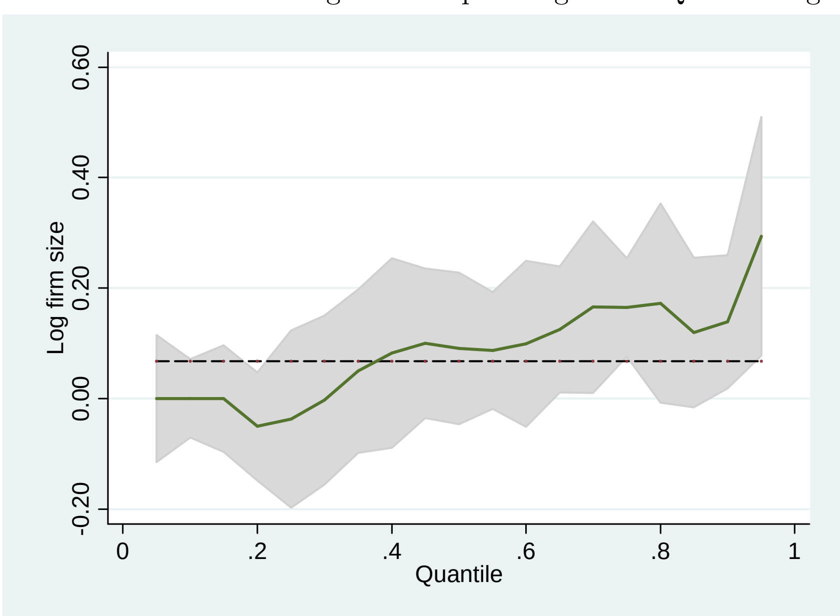
Note: Standard errors in parentheses. Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable is the logarithm of expected number of employees in 5 years time.
The table reports (1) OLS, (2) quantile regression, (3) quantile regression with bootstrapped standard errors using 500 draws and (4) quantile count regression estimates for q=.75.

Table 6: Transition into entrepreneurship and entry in the same industry. IV estimates

Transition into entrepreneurship	(1) 2sls	(2) liml	(3) ivprobit	(4) probit
Log firm size	-0.0183	-0.0189	-0.181	-0.0305*
	(0.02)	(0.02)	(0.13)	(0.01)
Observations	3948	3948	3948	3948
F-stat. (excluded instruments)	10.75	10.75	.	.
Entry same industry	**(5) 2sls**	**(6) liml**	**(7) ivprobit**	**(8) probit**
Log firm size	-0.0135^{+}	-0.0136^{+}	-0.354***	-0.115**
	(0.01)	(0.01)	(0.03)	(0.04)
Observations	3824	3824	3824	3824
F-stat. (excluded instruments)	11.32	11.32	.	.

Note: Robust standard errors in parentheses. F statistic refers to the instruments in the first stage of the IV estimation. IV probit estimates by ML for which the first stage is not computed. All specifications control for Private, Age, Female, Graduate, Parents ever run a business and the intercept. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2: Expected growth. Quantile regression



Note: The figure shows the quantile regression estimates for the 0.75 quantile along with the OLS coefficient of previous employer's firm size on expeced firm growth: The solid line represents quantile regression coefficients and the shaded area the 95% confidence interval; the horizontal dotted line corresponds to the OLS estimate.

A Appendix. Data Description I

	Variables	Description
1	Log firm size	Number of employees working for the organisation in natural logarithms.
2	Private	Dummy taking 1 if the employer operates in the private sector.
3	Age	Age of the respondent at the time of the interview.
4	Female	Dummy taking 1 if the respondent is female.
5	Graduate	Dummy taking 1 if the respondent has a bachelor, masters or doctorate degree.
6	Parents run a business	Dummy taking 1 if respondent's parents ever run a business.
7	Project involves IP	Dummy taking 1 if any new intellectual property such as a trade mark, copyright or patent has been applied for as a result of the new business.
8	Same industry 3 digits	Dummy taking 1 if the ISIC three-digit code of the new venture is the same as previous employer's code.
9	Expected growth	Expected number of people, not counting the owners but including all exclusive subcontractors, working in the business in 5 years time in natural logarithms.

Note: For entrepreneurs, the questions refer to the employer they were last working for.

B Appendix. Data Description II

The identification of entrepreneurs and employees have been done following a set of standardised screening questions shown below.

- Individuals answering affirmatively to questions 1.1 or 1.2, 4, “all” or “part” to question 3 and responding “no” to question 3 are defined as entrepreneurs.
- Employees are identified as those answering “working full-time or part-time” and “working for someone else in a job” to question i or giving an affirmative answer to question ii.

Enrepreneurs
1.1- Over the past twelve months have you done anything to help start a new business, such as looking for equipment or a location, organising a start-up team, working on a business plan, beginning to save money, or any other activity that would help launch a business?
1.2- Are you alone or with others currently the owner of a business you help manage, or are you self-employed or selling any goods or services to others?
2- Do you personally own all, part, or none of this business?
3- Did the founders of the business receive any wages, profits or payments in kind from this business before 1 January 2007?
4- Are you in employment in addition to working on this new business, or were you in employment before you started working on this new business?
Employees
i- Which one of the following best describes your main employment status?
ii- Have you been employed by others at any time in the past two years?

Note: Available options to question i : Working full time/ Working part time/ A full time homemaker/ Retired and not in paid employment/ In full time education/ Registered long term sick or disabled/ Out of work at the moment, and claiming benefit/ Not working at the moment and not claiming benefit/ Full-part time carer/ Other/ Refused