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New dimensions on the economics of the entrepreneurial process

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Summary

This thesis examines the transition of employees into entrepreneurship, with particular emphasis on the role of workplace characteristics in influencing this movement. The first main chapter examines whether the determinants of becoming an intrapreneur differ from those that support transitions into independent entrepreneurship. The results show that intrapreneurs resemble employees rather than entrepreneurs, contrary to what the entrepreneurship theory would suggest. Yet it shows that those intrapreneurs that expect to acquire an ownership stake in the business, unlike the rest of intrapreneurs, possess traditional entrepreneurial traits. Chapter 3 investigates how workers' degree of specialisation determines their decision to found a firm. It shows that entrepreneurs emerging from small firms, i.e. generalists, transfer knowledge from more diverse aspects of the business and create firms more related to the main activity of their last employer. Workers in large firms, however, benefit from higher returns to human capital that increase their opportunity costs to switch to entrepreneurship. Since becoming an entrepreneur would make part of their specialised skills unutilised, the minimum quality of the idea at which they would be willing to leave will be higher and, therefore, entrepreneurs emerging from large firms will be of highest quality. Chapter 4 analyses whether the reason to terminate an employment contract is associated with the fact that the majority of entrepreneurs appear to set up their business after having worked for a small firm. Moreover, it studies how this pattern varies as the labour market conditions worsen. The effect of layoffs turns out to be a key driver in the entry to entrepreneurship and it is found to exert a greater effect the smaller the firm workers are dismissed from. This has been reflected in an overall larger flow of employees from small firms moving into entrepreneurship over the recession.

Keywords: Entrepreneurship, Self-employment, Human Capital, Mobility, Occupational Choice

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Chapter 1

Introduction

Roughly 85% of the entrepreneurs in developed countries were or are still in employment at the time they launch their own business[1]. This raises a question on how the decision to set up a firm is influenced by their employment experience at the incumbent firm. This is of even greater importance in light of the fact that half of these entrepreneurs pursue a business idea they encountered through their experience as an employee. Whereas understanding the decision to become an entrepreneur, as opposed to paid-employment, has been a central question for researchers for many decades, the literature on entrepreneurship has been silent about the impact of incumbent firms in generating and shaping the entrepreneurial process until recently. Not only that, but we still also know little about why some ideas are developed within the existing organisation while others are taken forward by employees leaving to set up a spinoff[2]. This is, broadly said, the underlying and unifying theme across the three independent chapters that comprise my thesis.

One class of explanations that has been proposed to explain the formation of spinoffs highlights the influence of workplace characteristics in shaping the abilities and attitudes towards entrepreneurship among prospective entrepreneurs. This would

[1] According to data from the Global Entrepreneurship Monitor 2012, in its special topic on Intrapreneurship and Spinoffs.

[2] Note that here the term spinoff will refer to the new businesses created by employees who were or are still in employment before setting up the business. Thus, the distinction between spinoffs and other *de novo* modes of entry, namely independent start-ups, lies in previous employment ties. Other terms such as spin-outs or employee entrepreneurship activities have been also used in the literature to refer to the same phenomenon. When spinoffs enter the same industry as their founders were last working in these will be referred as intra-industry spinoffs (Helfat and Lieberman, 2002; Klepper, 2001).

determine their probability to quit the firm to pursue their career or lifestyle goals through entrepreneurship (Sorensen, 2007; Parker, 2009b). Another view, however, posits that spinoffs reflect limited capabilities of incumbent firms in capturing the rents of the ideas generated within the organisation (Gompers *et al.*, 2005; Sorensen, 2007). Spinoffs could emerge following strategic disagreements between the entrepreneur and the employer on how to develop and manage the new business or aspects related to the reward scheme (Klepper and Thompson, 2009). Likewise, incumbent firms may reject developing certain ideas because they lie outside the core expertise of the firm, which implies that they may even fail to properly evaluate and select most promising projects in the first place.

On the other side of the coin, however, incumbents can promote the generation and development of entrepreneurial activities by existing employees in the firm, which are referred as intraprepreneurial activities. These can emerge as a result of employee's proactive bottom-up initiatives or rather firm's effort to promote the generation of new businesses or the renewal of the firm. In the former case, ideas can be developed within the same organisation or taken in an independent self standing venture where the incumbent retains a financial interest.

Although intrapreneurial activities and the formation of spinoffs are expected to be closely linked phenomena, especially in light of the mentioned stylised fact that most ideas developed in spinoffs were encountered in the workplace, the research streams studying each of them have developed separately. I therefore start my thesis connecting both literatures by examining individual level factors affecting the decision to engage in independent entrepreneurship versus intrapreneurship. Afterwards, building on the research on the economics of spinoffs, I move to analyse how workplace characteristics and the economic cycle influence the decision to leave a paid-job to set up a new business. While doing so, I mainly focus on learning theories to explain the formation of spinoffs and knowledge flows.

Chapter 2, entitled "What's so entrepreneurial about Entrepreneurs?" examines whether the determinants of becoming an intrapreneur, understood as getting involved in entrepreneurial activities within an organisation as an employee, are the same as those that support transitions into independent entrepreneurship. This allows us to observe if there is actually anything distinctive about the entrepreneurs who pursue the idea on their own. Although intrapreneurship encompasses two main phenomena, the creation of new businesses by existing organisations and the strategic renewal of firms (Sharma and Chrisman, 1999), I restrict the attention to individuals involved in generating and developing new business activities for their employer. Hence, the scope of intrapreneurship adopted in the study is closer to the concept of new venture creation, although the development of the idea may not lead to the formation of a new organisational unit (Miles and Covin, 2002). I rest on the utility maximisation framework to assess how the occupational choice is influenced by individuals' degree of risk aversion and subsequent expected earnings along with their entrepreneurial ability. In doing so, I step back from the usual view that intrapreneurs are merely a sub-category of entrepreneurs, but rather consider entrepreneurship as a continuum. Different occupations are then positioned along that continuum based on their degree of risk taking and autonomy they involve. The two extremes are independent entrepreneurship and paid-employment. Therefore, I analyse the occupational choice of individuals who decide among three occupations: independent entrepreneurship, paid employment and intrapreneurship. The data I use is drawn from the 2008 Spanish Global Entrepreneurship Monitor questionnaire, which includes additional questions about intrapreneurship and allows me distinguishing intrapreneurs from independent entrepreneurs and the rest of employees. I show that intrapreneurs resemble employees rather than entrepreneurs, contrary to what the literature would predict. Specifically, comparing the decision-making of intrapreneurs to that of entrepreneurs, the former are significantly more risk averse and are broadly endowed with a poorer set of entrepreneurial abilities as they seem to fail to recognise business opportunities and have lower confidence in their entrepreneurial skills. I also distinguish two subgroups within the category of intrapreneurship: intrapreneurs and engaged intrapreneurs. Given that the level of personal risks they bear differs greatly depending on whether they hold ownership of the new business I examine whether engaged intrapreneurs, or those who expect to acquire an ownership stake in the business, share the attributes usually assumed to characterise entrepreneurs. A very close version of this chapter has been accepted for publication in Small Business Economics.

While the analysis described above deals with individual level differences that determine the final occupational choice, the next two chapters consider that these can be actually an outcome of individuals' experiences in wage work which make them more or less likely to opt for entrepreneurship afterwards. In Chapter 3, entitled "Mobility of Skills and Ideas", I investigate how the composition of human capital that workers acquire on-the-job determines their decision to found a firm and the know-how that they exploit in the new business. I first present a theoretical model following the insights by (Hvide, 2009) to illuminate differences in the incentives to switch to entrepreneurship between workers in small and large firms, explained in this case by the task-specific skills they acquire and can transfer across firms. I theorise that workers in small firms are assigned a wider set of tasks, hence they accumulate balanced skills, contrary to workers in large firms who become specialists. Knowledge is portable across firms, or occupations, as long as the latter requires the performance of the same tasks as the original ones. This allows workers from small firms to transfer knowledge from being involved in a wide range of tasks in the incumbent firm to the new firm and create firms more related to the main activity of the firm where they had been working. Workers in large firms, however, benefit from higher returns to human capital while they remain in paid-employment, which increases 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 only those with the best ideas will be willing to quit their job to pursue the project on their own. As a result, I predict that entrepreneurs from large firms will outperform those coming from small firms. I test these predictions using a uniquely constructed dataset of individual entrepreneurs in the UK which provides retrospective information about their latest employment. This survey has been conducted as part of the UK Global Entrepreneurship Monitor questionnaire in 2010. The dataset offers some desirable qualities that have been until now unavailable for academic researcher in such a large scale, including the possibility to capture entrepreneurs who are creating a business while keeping a parallel wage work. So I first examine individuals' probability to engage in the setting up of a firm and I afterwards focus on entries within the same industry the worker has been last working. I observe that the effect of firm size is notably larger in the second case, which I conclude as an evidence of wider knowledge spillovers through employee mobility from small firms to start-ups. Using quantile regressions I show that entrepreneurs coming from large firms have higher employment growth prospects compare to entrepreneurs coming from small firms as the theory suggests. This chapter is published as a DRUID Working Paper (no. 12-04) and the 2012 edition of Frontiers of Entrepreneurship Research.

Chapter 4, entitled "Changing Labour Market Conditions: Employee Mobility and Entrepreneurship", following the results of Chapter 3, examines whether the reason of terminating an employment contract is associated with the fact that the majority of entrepreneurs appear to set up their business after having worked for a small firm. Moreover, it investigates whether this pattern varies as the labour market conditions worsen, by analysing the period prior to, and during, the latest recession in Spain. Spain constitutes an excellent scenario to study how the employee flows respond to labour demand shocks, in this case measured by the increase in dismissals and unemployment, due to the sharp rise in unemployment that has accompanied the recession. Although the unemployment rate before the crises was at similar level than in other European countries, Spain has experienced the largest employment loss relative to the fall in GDP (Gregg and Wadsworth, 2010). Apart from the longitudinal source of variation, I also exploit the fact that the difference in unemployment across regions is large and has widened over the recession. To do so, I use unemployment data of the 50 Spanish provinces. I derive the results using a matched employee-employer dataset that tracks the career history of a large sample of individuals from Spain. As opposed to earlier chapters, where I identify new business founders or intrapreneurs, here I study transitions into self-employment defined by their status in the Spanish Social Security records. The empirical findings provide evidence of the existence of the small firm size effect, which persists after controlling for the reason to terminate the employment contract. The effect of dismissals, or redundancies, from an existing employer turns out to be a key driver in these transition decisions of the individual and it is found to exert a greater effect the smaller the firm workers are dismissed from. This has been intensified even further in the current recession as we observe an overall larger flow of employees from small firms moving into entrepreneurship as the unemployment has surged. This means that most self-employed, and especially those working in small firms, opt for self-employment after a dismissal and when the alternative job offers become scarce.

While the three studies contained in this dissertation cover different aspects in the individual entrepreneurial entry decision using datasets drawn from different sources, namely survey and administrative data, the main message across all of them is that employment experiences in incumbent firms matter for entrepreneurial activity.

Chapter 2

What's so Entrepreneurial about Intrapreneurs?

2.1 Introduction

"Entrepreneurship in existing organisations" has been a widely used definition for intrapreneurship (Antoncic and Hisrich, 2003). Despite the existence of terminology differences in the literature, such as intrapreneurship, corporate entrepreneurship or entrepreneurial employee activities, (Sharma and Chrisman, 1999; Christensen, 2004), the recognition of intrapreneurial activities has widened the notion of entrepreneurship by incorporating entrepreneurial activities undertaken within established organisations to the usual view of entrepreneurship as new independent business creation.

In this chapter I investigate the determinants of becoming an intrapreneur. An important stream in entrepreneurship research has been interested in understanding the transition into entrepreneurship, as an alternative to paid-employment offered in the labour market (Stevenson and Jarillo, 1990); nevertheless, there has been little discussion about its consistency to explain individuals' intrapreneurial action to date. Recent attempts to understand the nature of intrapreneurship focus on factors that favour intrapreneurship over independent entrepreneurship, as a response to the substantial body of the literature that regards the former a sub-field of entrepreneurship (Matthews *et al.*, 2001; Antoncic and Hisrich, 2003). For instance, Parker (2011) shows evidence on individual level differences between nascent intrapreneurs and entrepreneurs in that for example, youngest and older employees are more likely to get involved in intrapreneurship activites rather than in the setting up of an independent venture. Moreover, although general human capital measures are found to increase the probability to engage in any of the entrepreneurial activities, once controlling for this selection, they seem to be positively associated with nascent entrepreneurship over nascent intrapreneurship.

In this study I extend this line of work by introducing paid employees in the analysis and asking whether intrapreneurs are actually similar to independent entrepreneurs or rather resemble a profile of employees. Here entrepreneurship is used as a synonym for autonomous venture set up whereas intrapreneurship refers to the generation and exploitation of new business ideas by employees in existing organisations, without assuming intrapreneurship a subcategory of entrepreneurship *per se*. More specifically, I define intrapreneurs as "the employees involved in the development of new business activities for their employer, such as establishing a new outlet or subsidiary, or launching new products and new product-market combinations for an existing organisation". Intrapreneurship has been most widely accepted to encompass the development of new markets or products that lead to the creation of new ventures but also the strategic renewal or transformation of firms (Sharma and Chrisman, 1999). The definition adopted in this work is therefore closer, although broader, to the former, as it excludes many of the activities that result in renewing the firm, such as the re-combination of existing assets to achieve greater efficiency. I conduct, therefore, the comparison separately for each of the entrepreneurial groups: independent entrepreneurs and individual intrapreneurs. By doing so, I expect to find strong similarities between employees and intrapreneurs as they both work within the boundaries of a firm, yet I test their resemblance to entrepreneurs as they are, almost by definition, engaged in entrepreneurial behaviour and actions.

Following the utility maximisation theory I explore why individuals decide to be either independent entrepreneurs, employees or intrapreneurs. Modern economic theories of entrepreneurship target occupational choice models subject to heterogeneous specific personal characteristics, usually risk aversion or managerial talent (Parker, 2004). Douglas and Shepherd (2000; 2002) argue that people's attitudes toward risk, independence and expected income explain their motivation to become self-employed. Based upon this framework Monsen *et al.* (2010) analyse the decision making of potential intrapreneurs by including risk taking and work effort behaviours as moderating factors in a financial utility maximisation model. I merge these views and build a joint occupational choice model where the decision making of individuals is driven by a combination of their expected financial reward, entrepreneurial ability and attitudes towards risk.

The study makes two main contributions to the literature. First, I introduce a novel distinction within the category of intrapreneurship. I consider the timing and the degree of engagement in intrapreneurial activities within the notion of intrapreneurship as a continuous process that implies further commitment and risk taking for the intrapreneur as the project develops (Antoncic and Hisrich, 2003). This is particularly true for those employees that initially get involved in seeking new business opportunities for their employer and end up creating and owning part of the new venture. So conceptually, this distinction narrows down the scope of intrapreneurship to the creation of new ventures, most likely taking the form of a semi-autonomous entity. But more interestingly, it suggests that "engaged intrapreneurs", as I will refer to them, are on the frontier between paid-employment and entrepreneurship as they also become residual claimants. Yet, since both entrepreneurial processes differ in the associated implied risk and required managerial ability along the whole process of setting up the business, I expect individual level characteristics to also condition the transition into independent entrepreneurship over "engaged intrapreneurship". I, thus, include a fourth occupational category, namely "engaged intrapreneurs", which serves to test whether these individuals differ from the rest of intrapreneurs, who have decided to remain within the organisation and develop the business ideas for their employers, and the extent to which they resemble independent entrepreneurs.

Second, this study enriches the literature, mainly made up of theoretical studies to date, by presenting an empirical evidence of differing utilities across a broader set of occupational choices. So far, little empirical work exists on the determinants of intrapreneurship at the individual level of analysis, due to scarce data to make it feasible, and as far as I know there is no study undertaking a comparative analysis between these occupational categories together. The present study addresses this gap by using Global Entrepreneurship Monitor (GEM) data from Spain.

In what follows, section 2.2 presents the theoretical background supporting the hypotheses of income variability and expected market reward on the context of heterogeneous aversion to risk and I then consider the differing entrepreneurial ability among individuals in the four occupational categories. In Section 2.3 I discuss the empirical analysis and results from both descriptive and multinomial logit regressions. Section 2.4 concludes by summarising the main findings and limitations of the present study and makes suggestions for future research.

2.2 The Choice of Becoming an Intrapreneur. Theoretical Background

The main conceptual framework adopted here is the utility maximisation, which will represent the preferences of individuals over the financial reward and their degree of risk aversion. This allows going beyond the simpler financial maximising framework, as it captures further working conditions that generate satisfaction or dissatisfaction and therefore, explain individuals' career choice, which will be also conditioned by their entrepreneurial ability. Of course, this approach is still unable to consider other socio-psychological dimensions, such as group collectivism, that could influence the decision of quitting a firm to become an entrepreneur, yet it provides a simple and tractable framework to test empirically the predictions in the following section.

2.2.1 Risk Aversion and Expected Earnings

Heterogeneity of an individuals' aversion to risk and risk-adjusted labour market rewards was first proposed by Knight (1921). Modern approaches in this area are influenced by the later contribution of Kihlstrom and Laffont (1979), which suggests that more risk-averse individuals become employees and more risk-tolerant agents entrepreneurs. Empirical studies have shown, however, contradictory results regarding the influence of risk attitudes on entrepreneurial activity (Xu and Ruef, 2004; Blanchflower and Oswald, 1998; Parker, 2009a). These have been many times explained by the difficulties in measuring this aversion precisely and indeed separately from other psychological traits such as optimism and confidence (Caliendo *et al.*, 2009; Weber and Milliman, 1997; Arenius and Minniti, 2005). I conjecture here the most intuitive notion that risk adversity influences negatively entrepreneurial activity, as supported by many theoretical studies (Kihlstrom and Laffont, 1979; Praag and Cramer, 2001; Douglas and Shepherd, 2000; Landier, 2004).

Risk-taking behaviour has been also considered an aspect of intrapreneurship (Antoncic, 2003; Lumpkin and Dess, 1996; Monsen *et al.*, 2010; Antoncic and Hisrich, 2003) but contrary to autonomous entrepreneurship, risk is shared between the firm and the intrapreneur. The established firm can provide the intrapreneur support of different kinds. For instance, it may assume financial risk and offer operational and administrative assistance if necessary (Luchsinger and Bagby, 1987). In case of failure the intrapreneur may be reallocated to another position within the firm, while the entrepreneur suffers the cost of losing his job and having to search for a new one. Since contractual terms diminish the personal risks that intrapreneurs are required to assume, which primarily involve reputational and career advancement risks rather than financial risks, this may lead them to undertake higher risks than what they would have taken individually (Lumpkin and Dess, 1996; Antoncic, 2003).

Similarly, the choice to commit further in the corporate venture by acquiring an ownership stake may be determined by the disutility that intrapreneurs derive from additional risk bearing, as it will generally involve greater financial uncertainty and may also imply a risk of losing their job (Monsen *et al.*, 2010; Douglas and Shepherd, 2000, 2002). This results in the least risk-averse intrapreneurs being more likely to engage in the setting up of corporate spin-outs. In comparison to entrepreneurs, however, engaged intrapreneurs do not bear the total risk of profits and losses along the entire process of the project development, as entrepreneurs do, especially throughout the process of searching for opportunities and liaising with their employer. Risk-taking behaviour therefore constitutes a distinguishing characteristic of entrepreneurs and may imply the reason that engage entrepreneurs are not willing to involve in autonomous start-up.

> H1: Individuals showing greater risk aversion are less likely to engage in entrepreneurial and more autonomous occupations such as independent entrepreneurship and engaged intrapreneurship.

This theoretical approach makes the relationship between risk-taking behaviour and market rewards central to understand entrepreneurial entry. Given that individuals seem to sort themselves into different occupations based on their preferences towards risk, a risk premium, namely the entrepreneurial premium, would be necessary for intrinsically risk-averse individuals to engage in entrepreneurial projects (Petrakis, 2004; Kihlstrom and Laffont, 1979). If we think of a wage-risk framework, wages are determined in equilibrium by the the locus of tangencies between individuals' utility and firms' isoprofit curves. So individuals confront the trade-off between higher returns with greater levels of risk and safer but lower earnings and they choose the combination that provides them the highest utility. In the presence of workers with different preferences for risk, hence differences in the slopes of their indifference curves, higher wages will only outweigh the disutility of risk of more risk-tolerant individuals. Therefore, since individuals are required to assume different risk levels across our categories of interest, as noted in the Hypothesis 1, this will lead us to observe earning differences across the occupational choices.

> H2: Both intrapreneurs and engaged intrapreneurs are more likely to demand lower remuneration than entrepreneurs but higher than employees.

2.2.2 Entrepreneurial Ability

There is evidence that entrepreneurial ability also enters into the decision to become an entrepreneur (Gimeno *et al.*, 1997; Lucas, 1978; Murphy *et al.*, 1991). Lucas's (1978) seminal paper motivated later models in occupational choice on the basis of a continuous distribution of entrepreneurial talent among the workforce. He offered an explanatory model for the division between employees and managers (entrepreneurs), where less talented individuals that share common skills are employees, and above a certain ability threshold level some people become entrepreneurs. Skill, according to Lucas (1978), is defined as managerial talent and understood to be an innate and exogenous virtue of individuals.

In broad terms, entrepreneurial ability comprises the human capital required to perform tasks that entrepreneurs undertake but also the ability to recognise emerging business opportunities in the market. Empirically, human capital (Becker, 1964) has been usually measured by the formal educational attainment and the job market experience, which allows acquiring the skills to start a business. Empirical studies assessing the linear impact of additional years of education on entrepreneurial entry, however, have been conflicting (van der Sluis *et al.*, 2008) and find greatest support for an inverse U-shape relation between entrepreneurship and educational attainment as a proxy of ability (Blanchflower, 2000; Poschke, 2008).

Lazear (2005), however, discusses how the range of skills, instead of the depth of the knowledge or higher levels of education, relates to the likelihood of an individual to engage in entrepreneurial activities. He argues that entrepreneurship requires a wide range of knowledge and skills to perform the different roles involved in setting up a new venture, so individuals not simply with higher educational attainment but with more balanced skills are more likely to become entrepreneurs. This leads potential entrepreneurs to invest in a more balanced general human capital through their formal education and diverse professional experience. This "jack-of-all-trades" view of entrepreneurs does somehow contradict the notion of innovative entrepreneurs, who are believed to have specific and deep knowledge on a particular technology or industry (Marvel and Lumpkin, 2007). Nevertheless, we could expect specialists or individuals without such balanced skills, or who possess lower managerial skills, to become intrapreneurs or engaged intrapreneurs since the organisation will offer them support on those skills they have not been trained on. Therefore, they can better perform in the task of exploiting the business opportunity by concentrating on their specialist skill sets.

But it is not just objective skills but also the self-assessment of entrepreneurial abilities that is correlated with entrepreneurship (Arenius and Minniti, 2005). Due to the predominance of overly optimistic attitudes among entrepreneurs, skill perceptions are also likely to be biased, and as a result entrepreneurs may over-estimate their chances to succeed and to pursue profitable opportunities too often (Camerer and Lovallo, 1999). This could explain some of the contradictory empirical findings on the relationship between human capital measures and entrepreneurial activity and could actually determine the tipping point between wage work and self-employment. Furthermore, if an intrapreneur perceives his entrepreneurial talent to be high, he may demand an ownership stake in the business and become an engaged intrapreneur. In this case, a spin-off rather than a new business unit within the firm is more likely to occur.

> H3a: Entrepreneurship and engaged intrapreneurship are positively associated with a more balanced pool of skills and self-perception of entrepreneurial skills.

On the basis of the Kirznerian view of the entrepreneur as an opportunity seeker, individuals need to be alert to recognise business opportunities in the market (Kirzner, 1997, 1999). Yet, as pointed out by Parker (2011) intrapreneurs may solely act in response to a request by their employer, meaning that they would not otherwise have engaged in seeking and developing business opportunities, presumably because their lack of proactiveness to do so. In addition, both engaged intrapreneurs and intrapreneurs may have a narrow scope of market opportunities, constrained to business ideas that relate to the core competences of the parent firm, whereas independent entrepreneurs are able to operate and search for ideas in a wider set of industries and markets.

The perception about existing business opportunities can be, however, the result of individuals' alertness and ability to recognise them along with their capacity to assess their feasibility realistically. Given, as mentioned earlier, that entrepreneurs are characterised by optimistic attitudes, we could expect entrepreneurs to over-estimate existing business opportunities as well.

> H3b: Entrepreneurs recognise more business opportunities than engaged intrapreneurs, intrapreneurs and employees.

2.3 Empirical Analysis

2.3.1 Sample

This section tests empirically the above hypotheses using the Spanish Global Entrepreneurship Monitor (GEM) data. This research programme assesses entrepreneurial activity at national and regional level on an annual basis (Reynolds *et al.*, 2005) and collects data through telephone surveys of a randomly selected adult sample on their involvement and attitudes toward entrepreneurship. Apart from the core set of questions asked each year, additional questions are included in the survey every year to cover different areas within entrepreneurship research. Data used in this work is obtained from the Spanish GEM 2008 survey which addressed the special topic of intrapreneurial activity and allowed me to differentiate for the first time intrapreneurs from independent entrepreneurs and the rest of employees, as well as providing additional information about intrapreneurial activities.

Based on the screening questions and business ownership information in GEM I define each occupational category as follows. Intrapreneurs refer to employees who reported to "have been involved in the development of new business activities for their employer, such as establishing a new outlet or subsidiary, or launching new products and new product-market combinations for an existing organisation during the last two years"[1]. Thus, I initially consider a broad definition of intrapreneurship, without assuming business ownership a necessary requirement to classify employees into intrapreneurs. But as discussed above, as business projects develop some of them will remain under the ownership and control of the established organisation, while other projects will operate as free-standing firms run by venture managers that acquire an ownership stake in the business. For this reason, and following the usual definition in GEM (Reynolds *et al.*, 2005), I do apply the ownership criteria when defining engaged intrapreneurs and entrepreneurs. In both cases, individuals are trying to start a new business that is up to 42 months old and expect to take part or full ownership in the

[1] Specifically, 70% of the intrapreneurs said to participate in projects in an advanced stage of development, so that their tasks included activities such as promoting the idea, preparing a business plan, developing marketing activities and searching for funding sources, whereas the rest of intrapreneurs were still developing ideas and searching for information to transfer them to their directors.

business. In other words, they meet the criteria to be part of the definition of nascent entrepreneurial activity calculated each year by the GEM project. However, engaged intrapreneurs perform the activities for their employer, as part of their usual work, while entrepreneurs indicate that they are trying to start a new business independently of their work. Previous empirical studies addressing differences across the two entrepreneurial categories have also analysed differences between nascent intrapreneurs and nascent entrepreneurs (Matthews *et al.*, 2001; Parker, 2011), since it allows comparing both categories at the development stage and captures not just self-employment but new venture founders.

Ideally, I would track intrapreneurs throughout the development of the project in order to assess who finally leaves the firm to manage the business independently, but unfortunately the GEM methodology consists of annual cross-sectional samples. It does provide, however, information to consider an alternative approach to understand part of the dynamics between paid- and self-employment through the introduction of a new category (engaged intrapreneurs) defined by a greater degree of engagement through business ownership participation.

Screening questions to identify intrapreneurs were carried out on employees that were neither owner-managers of the firm they worked for, nor classified as entrepreneurs in the initial screening questions. Therefore, the four occupational groups defined above are discrete and do not overlap in the sample. Thus, from the total dataset 113 individuals were identified as intrapreneurs, 615 were classified as independent entrepreneurs, 1,887 employees[2] and 339 as engaged intrapreneurs.

2.3.2 Descriptive Analysis

With regard to the variables used in the analysis, theoretical predictions suggest that a range of factors are related to the decision-making process of an individual to become an entrepreneur. These are described in detail in table 2.1.

[2]This extension about intrapreneurship of the Spanish GEM survey in 2008 was carried out on a subsample of 2,000 employees, out of the total 30,879 Spanish interviews and enables discrimination of intrapreneurs from employees solely in this smaller sample. For empirical analysis this reduces the initial sample of employees from 17,784 to 1,887 observations, since I am unable to separate intrapreneurs from general employees in the rest of the sample. The excluded subsample, therefore, consists of the pooled sample of wage earners, retired, students, inactive and owner-managers of established businesses.

Specifically, I include the dummy variable *Fear of Failure* as a proxy for risk aversion, which takes a unit value if the respondent agrees that the fear of failure would prevent him from starting a business and as the theory predicts. I am aware that this measure of risk aversion, as some of other attitudinal variables presented below, may present a cognitive dissonance problem (Bertrand and Mullainathan, 2001). In other words, individuals may be tempted to reveal attitudes that are consistent with their past actions, as in this case for example, on their decision to start a business. Hence, we could expect entrepreneurs and engaged intrapreneurs to report negative answers to this question. However, as in other studies across countries and years (Wagner, 2007), this is not supported by the data. Other studies have attempted to measure risk aversion through individuals' risk preferences over lotteries (Praag and Cramer, 2001; Xu and Ruef, 2004) or psychometric tests (Ekelund *et al.*, 2005), which allow to overcome the mentioned concerns, but these are not available in the present dataset. Yet, note that the analyses between entrepreneurs and engaged intrapreneurs on one side, and intrapreneurs and employees on the other side, are free from this potential bias and are still of the interest in this study.

Following the theory, I expect higher income levels (*lnIncome*) to be correlated to occupations that involve a greater uncertainty in earnings. Since, GEM surveys do not collect data on individual income levels, I use household income data instead.

The group of *Entrepreneurial ability* variables contain three dummy variables that permit exploring objective general human capital indicators, namely whether the respondent has received training on business creation or not (*Training business creation*) and highest educational attainment (*Graduate studies*), as well as self-reliance on personal skills for business creation (*Perceived start-up skills*). Distinguishing between specialised and balanced skills to test the Hypothesis 3a would require information about the roles that would-be entrepreneurs performed during their career history or the courses that constituted their educational curriculum (Silva, 2007; Lazear, 2005; Wagner, 2007), which are not available in this dataset. Alternatively I use *Training in business creation* as a proxy for the generalised skills, so I assume that courses on business creation contain modules from a variety of fields, necessary to build up wider entrepreneurial skills. Similarly, *Opportunity recognition* represents personal beliefs about the existence of good business opportunities in the market in the six months ahead. Finally, a set of demographic variables are introduced for control purposes (i.e., age and gender).

Table 2.2 provides descriptive statistics for the four occupational categories in the sample and shows first evidence of the similarities and differences across the groups. The last column for each occupation, i.e. entrepreneurs, employees and engaged intrapreneurs, comprise differences in means between intrapreneurs and the corresponding category. Given that levene's test for the equality of variances suggests inequality in variances, with just a few exceptions at 5% significance level, independent samples t- tests are performed to compare means.

As expected, intrapreneurs are significantly more risk averse than entrepreneurs, earn lower income, perceive less business opportunities in the short term and do not consider that they have enough skills to succeed in setting up a business, results that show evidence for Hypotheses 1, 2 and 3b.

These results are almost identical to those I obtain when comparing intrapreneurs to engaged intrapreneurs and corroborates the idea that more entrepreneurial and riskier occupations require specific individual characteristics to succeed; hence not all intrapreneurs will be able and willing to deal with greater responsibility in the venture. However, employees, somewhat counter-intuitively, seem to observe more business opportunities than intrapreneurs, a result that could be interpreted by the weak motivational factors and pessimistic beliefs about the quality of the project by the latter. These tests do not consider any interaction among the variables, they do nevertheless provide insight into the differences across the four occupational groups. The most striking observation to emerge from here is that the two categories of intrapreneurs appear clearly distinguished, engaged intrapreneurs bearing a greater resemblance to autonomous entrepreneurs and less committed intrapreneurs more likely to resemble the profile of employees.

2.3.3 Regression Specification

In this section I apply the multinomial logit model to predict the likelihood of an individual choosing an occupational category given their entrepreneurial ability and attitudes[3]. I expect individuals to choose their occupation by maximising their expected utility defined as:

$$U_i = \alpha + X_i^{'}\beta = \alpha + \beta_0 FinancialUtility_i + \beta_1 RiskAversion_i + \beta_2 EntrepAbility_i + Z_i^{'}\beta_3$$

And we estimate:

$U_i = \alpha + \beta_0 lnIncome_i + \beta_1 FearofFailure_i + \beta_2 TrainingBusinessCreation_i + \beta_3 Graduate_i + \beta_4 PerceivedStart-upSkills + \beta_5 OpportunityRecognition_i + Z_i\beta + \varepsilon_i$

Where the first variable measures the household income in logarithms, followed by a risk aversion proxy and variables determining the entrepreneurial ability (human capital and market opportunity perceptions), and finally, a set of demographic control variables denoted by Z. Thus, and assuming i.i.d., extreme value distributed error terms, I estimate the multinomial logistic model as follows (Greene, 1992):

$$p_{ik} = Pr(y_i = k) = \frac{\exp(\alpha + X_{ik}^{'}\beta)}{\sum_{j=1}^{4}\exp(\alpha + X_{ij}^{'}\beta)} k = 1, 2, 3, 4$$

A categorical dependent variable is defined so that it takes on four levels (1 for intrapreneurs, 2 for entrepreneurs, 3 for employees and 4 for engaged intrapreneurs) and weighted data are used to correct for unbalanced groups and missing responses[4].

[3]Missing values for some of these variables will limit the size of the sample in the following regression analyses.

[4]Due to the methodology to identify intrapreneurs employed in GEM, as explained in footnote 2, entrepreneurs were overrepresented in the sample: while the ratio of entrepreneurs over the total sample of employees represented 3.5% (615/17,784), the ratio was significantly higher (30.7%) over the subsample of employees (315/2,000). I overcome this issue by weighting the data by their inverse sampling probability so that each occupational category matches its real proportion in the population. Unweighted regressions provided similar results.

2.3.4 Results

The results of the multinomial logit regression are reported in the table 2.3 for each pair of comparison groups in terms of the relative risk ratios or exponentiated coefficients. Again, intrapreneurs are compared to each alternative occupation that is set as the base category in columns 1 to 3. I will comment only on the results that help us understand the nature of the intrapreneurial process, and omit other interpretations that could be interesting in another context, for example, by comparing entrepreneurs and employees.

The first column shows that a higher fear of failure significantly increases the probability of becoming an intrapreneur over an independent entrepreneur holding all else constant and reaffirms the Hypothesis 1 that intrapreneurs are more risk averse than entrepreneurs. However, compared to employees and engaged entrepreneurs, although the relative risk ratios are also greater than unity, suggesting intrapreneurs' greater risk aversion, the estimates are not statistically significant.

The results on the income variable (lnIncome) are consistent with Hypothesis 2, indicating that higher income is associated with riskier occupations, that is, higher income levels predict entrepreneurial or engaged intrapreneurial options over the intrapreneurial career and confirms that financial reward is necessary for individuals to assume greater personal risks. Previous studies on corporate venturing reward schemes have also found that, for instance, the likelihood of individuals participating in intrapreneurial activities increases when higher profit-sharing terms are introduced (Monsen *et al.*, 2010) and that variable bonuses based on return on investment are the preferred compensation schemes among venture managers (Block and Ornati, 1987).

I find that intrapreneurs differ from entrepreneurs on their entrepreneurial ability and in the same direction as the theory predicts (Hypothesis 3a and 3b). For example, greater opportunity recognition and self-perception of entrepreneurial skills significantly decrease the relative risk for the choice between intrapreneurial and entrepreneurial outcomes. In other words, intrapreneurs are less likely to perceive they have the necessary start-up skills and that there are good opportunities for start-up in the market in the next 6 months. The comparison between intrapreneurs and employees in column 2 shows that short-term opportunity recognition is negatively associated with the choice to engage in intrapreneurship. As mentioned earlier, the fact that some intrapreneurs may get involved in the projects at the request of their employer or another colleague could explain their lack of alertness and more negative perception of market opportunities (Parker, 2011). Interestingly, training in starting a business after completing official schooling (i.e., post-secondary education), turns out to be significant and more likely to be associated with intrapreneurship rather than entrepreneurship. This variable could reflect a more balanced or diverse formal training necessary for start-up and would reject part of the Hypothesis 3a that balanced human capital is linked to independent entrepreneurship. This is somewhat surprising as I would have expected entrepreneurship training to encourage people to cross the frontier into entrepreneurship. But it may reflect something else; it may encourage people to be enterprising beyond the usual conception, that is, in the context of an established business.

Turning now to the predicted differences between intrapreneurs and engaged intrapreneurs, column 3 reaffirms the trend already observed in the descriptive analysis: the variables of interest (*Fear of failure, lnIncome, Training in business creation, Graduate, Perceived start-up skills and Opportunity recognition*) exert almost an identical effect on the decision-making between intrapreneurs over entrepreneurship as over engaged intrapreneurship. Given that these results suggest a clear distinction between the two intrapreneurship categories and point intuitively towards a greater resemblance between engaged intrapreneurs and entrepreneurs, I now consider the probability of becoming an engaged intrapreneur over an independent entrepreneur.

The factors underlying the probability of choosing engaged intrapreneurship over entrepreneurship differ from those observed for the choice of intrapreneurship. As shown in table 2.4 observing good business opportunities in the market increases the likelihood of getting involved in independent entrepreneurship. However, having a university-level degree now exerts a significantly positive effect on engaged intrapreneurship while the rest of the human capital measures (*Perceived start-up skills* and *Training in business creation*) turn out to be non-significant in the model and do not provide evidence for the prediction on balanced human capital skills.

So far, I have discussed results that were statistically significant and which supported (or not) my predictions set out in the hypotheses. I now move on to explore the magnitude or the economic significance of these effects. For this purpose I plot discrete change coefficients, which indicate how a unit increase, i.e. one standard deviation change for continuous variables and a unit change for dummy variables, affects the probability of choosing each of the occupations holding the rest of the variables at their mean value (Long and Freese, 1997). The four occupational categories are labelled as before: intrapreneurs (I), entrepreneurs (E), employees (M) and engaged intrapreneurs (N).

Figure 2.1 reveals that the effect of entrepreneurial ability, in particular the effects of perceived start up skills and the ability to observe business opportunities, is the largest predictor of occupational choice and especially increasing the probability of riskier occupations. Recognising business opportunities in the short-term increases the likelihood of becoming an entrepreneur by 0.054. A slightly lower absolute positive change (0.045) is associated with the perception of having enough knowledge and skills for start-up, while this effect substantially decreases the probability of becoming an employee (-0.070). The corresponding effects on the probability of engaging in intrapreneurial activities are in the same direction of entrepreneurship but of a lower magnitude. The effect of entrepreneurship education is large in predicting the probability of intrapreneurship. Similar calculations as before show that training in business creation is associated with an absolute 0.037 increase in its probability.

I have undertaken a large variety of robustness tests. One of the caveats of the multinomial logit model is that it requires the irrelevance of independent alternatives (IIA) to hold (Train, 2003), that is, it requires that the preference of selecting one occupational over another to be independent of the existence of any other alternative. I have conducted a Hausman test to assess if this is actually the case and confirmed that the IIA assumption is not violated at the 5% significance level. Moreover, in order to relax this strong and many times unrealistic restriction in the substitution patterns, and given that the Hausman test is only reliable under homoskedastic residuals, I have re-estimated the models using the multinomial probit specification. The results have confirmed the robustness of the logit specification. All results are also robust to including additional demographic variables, such as regional dummies, household size and urban-rural origin of respondents[5].

Finally, one central issue in the formulation of the conceptual discussion and empirical analysis presented here is whether intrapreneurs resemble any occupational group not included in the model. Over half of the intrapreneurs reported that they performed a leadership role in the project, suggesting an interesting comparison to middle managers not involved in corporate venturing activities rather than the pooled sample of employees might be a fruitful line of inquiry. However, I am unable to identify managers with no involvement in the ownership of the business separately from other owner-managers in the sample, and hence I have conducted a comparison test between intrapreneurs and owner-managers of established firms (more than 42 months in operation) that are also surveyed as part of the GEM survey. Overall, and not surprisingly, the results are similar to those obtained from the comparison of intrapreneurs with entrepreneurs and conclude that owner-managers reflect the profile of successful independent entrepreneurs´ attitudes and abilities.

2.4 Conclusions

This chapter has been designed to investigate the determinants of becoming an intrapreneur. Based on the definition that intrapreneurs are individuals involved in the formation of new businesses within the boundaries of an existing organisation, that is, in broad terms a form of corporate venturing, the chapter questions their similarity with independent entrepreneurs and asks whether they are more likely to resemble the profile of employees.

The results presented here have gone some way towards enhancing our understanding of the process of intrapreneurship. The existing literature on intrapreneurship has underestimated the role and impact of individual intrapreneurs and poorly understood their incentives to participate in corporate venturing activities. Indeed, intrapreneurs

[5]Results are available upon request.

are generally thought of as a sub-category of entrepreneurship, without the necessary supporting evidence. I argue that a distinction within the category of intrapreneurship, based on the level of engagement and, therefore, the level of personal risks that they are required to bear, sheds some light on the concept of intrapreneurship. I find that engaged intrapreneurs, a term which is meant to encompass intrapreneurs who expect to acquire an ownership stake in the business, unlike the rest of intrapreneurs, share the attributes usually assumed to characterise entrepreneurs.

Second, following the utility maximisation theory I provide empirical evidence to show that intrapreneurs resemble employees rather than entrepreneurs, a fact that should be taken into account in future theoretical developments on the definition of intrapreneurship. Specifically, comparing the decision-making of intrapreneurs to that of entrepreneurs, GEM data for Spain suggests that intrapreneurs are significantly more risk averse, expect a lower but less uncertain reward and are broadly endowed with a poorer set of entrepreneurial abilities; despite having higher levels of human capital they fail to recognise business opportunities and have lower confidence in their entrepreneurial skills. My findings are consistent to those of Parker (2011) who found that those unobserved variables explaining the self-selection of individuals into intrapreneurial or entrepreneurial activities, also supported the choice of nascent entrepreneurship over nascent intrapreneurship. The present study also shows greater similarities between intrapreneurs and employees and reaffirms the idea that the former have a significant preference for paid-employment and may lack the necessary skills and attitudes commonly attributed to independent entrepreneurship.

I have also argued that the same factors driving the decision to become an entrepreneur are also associated with the choice of switching to engaged intrapreneurship. Thus, I stress the fact that the aggregation of the different sub-groups of intrapreneurship should be made with caution in future works developing the individual intrapreneurship literature. An important managerial implication is that suitable reward schemes should differ for each type of intrapreneurial activity. As pointed out by Monsen *et al.* (2010) profit sharing contracts have an increased effect on the willingness to participate in corporate venturing activities when both pay and the risks of job security are lower. Taken together, I argue that the reaction to profit sharing contracts will not be homogeneous among all intrapreneurs, but could be used to attract the ablest and less risk-averse employees to participate in riskier projects.

I am also aware of some of the limitations of the study that may have influenced the results. I am concerned about endogeneity issues between the choice of the occupation and the variables considered as independent in the model, such as income, fear of failure or perceived entrepreneurial skills, as these are not observed *ex ante*. In particular, this problem would have affected the comparison between paid employees and the rest of entrepreneurial groups, for example, when asking about the impact of fear of failure in their decision to start a business. Moreover, in many cases the distance between the theorical constructs and the variables I have used in the empirical models might be a concern, especially when these refer to individuals' attitudes, such as risk aversion, income or breadth of skills. For example, while I have used *Fear of Failure* as a measure for risk aversion one could also argue that it only refers to the downside risk and ignores the upside potential that new businesses entail. Likewise, I would have ideally used the number of previous employment roles or breadth of their education curriculum (Lazear, 2005) as better measures for balanced skills, however these were not available in the dataset. Additionally, I may be omitting significant variables not provided by the GEM survey, such as work experience, tenure, or industry categories as well as information concerning the precise contractual terms between intrapreneurs and their employers that would help understanding the potential transition from paid-employment into entrepreneurship. Indeed, I have addressed the occupational choice from a static view, so a natural step would be to allow flows across occupations over time.

Further questions remain regarding the optimal decision for the parent company on whether to develop the projects internally or rather to spin-out an independent venture through the vehicle of a former employee. In line with the concept of engaged intrapreneurship, this would relate to the incentives structure at the corporate level which would interplay with those of the employee to allow intrapreneurs to participate as an owner of the new venture.

In conclusion, most individual intrapreneurs are found to be vaguely entrepreneurial based on the traditional entrepreneurial traits, such as risk aversion, opportunity recognition and self-perception of entrepreneurial skills. We are left, however, with the evidence that intrapreneurs are a heterogeneous group and their level of engagement in the business yields a valuable insight into their decision to make further commitments.

Table 2.1: Description of variables

	Variables	Description
Risk-Related Variables		
1	lnIncome	Total income of household in natural logarithms.
2	Fear of failure	(1,0) dummy taking value one if respondent answered yes to: Would fear of failure prevent you from starting a business?
Entrepreneurial Ability		
3	Training business creation	(1,0) dummy training in starting a business after completing education in school.
4	Graduate	(1,0) dummy if graduate or postgraduate educational attainment.
5	Perceived start-up skills	(1,0) dummy taking value one if respondent answered yes to: Do you have the knowledge, skills and experience required to start a new business?
6	Opportunity recognition	(1,0) dummy taking value one if respondent answered yes to: In the next six months will there be good opportunities for starting a business in the area where you live?
Demographic Controls		
7	Male	(1,0) dummy if male.
8	Age	Age at time of interview.
9	Know entrepreneur	(1,0) dummy taking value one if respondent answered yes to: Do you know someone personally who started a business in the past 2 years?
10	Household size	Total size of household including respondent.
11	Urban	(1,0) dummy if urban residence.

Table 2.2: Descriptive statistics

	(1) Intrapreneur			(2) Entrepreneur				(3) Employee				(4) Engaged Intrapreneurs			
	N	mean	SE	N	mean	SE	diff	N	mean	SE	diff	N	mean	SE	diff
lnIncome	77	10.00	0.08	560	10.26	0.02	0.26***	1299	9.92	0.02	-0.08	299	10.26	0.03	0.26***
Fear of failure	111	0.57	0.05	601	0.31	0.02	-0.26***	1830	0.52	0.01	-0.05	333	0.34	0.03	-0.23***
Training bus. creation	113	0.18	0.04	612	0.21	0.02	0.03	1881	0.14	0.01	-0.04	337	0.25	0.02	0.08
Graduate	113	0.34	0.04	615	0.29	0.02	-0.04	1887	0.36	0.01	0.02	339	0.37	0.03	0.03
Perceived su skills	111	0.50	0.05	609	0.89	0.01	0.38***	1774	0.48	0.01	-0.02	333	0.90	0.02	0.4***
Opport. recognition	87	0.08	0.03	531	0.50	0.02	0.42***	1514	0.17	0.01	0.09**	285	0.43	0.03	0.35***
Control variables															
Male	113	0.46	0.05	615	0.54	0.02	0.08	1887	0.45	0.01	-0.01	339	0.60	0.03	0.14***
Age	113	42.39	0.98	615	40.69	0.46	-1.70	1887	41.08	0.25	-1.31	339	41.15	0.62	-1.24
Know entrepreneur	110	0.35	0.05	608	0.58	0.02	0.22***	1883	0.37	0.01	0.01	336	0.66	0.03	0.30***
Household size	113	3.15	0.09	615	0.82	0.02	0.09	1845	3.24	0.03	0.09	339	3.26	0.07	0.11
Urban	113	0.84	0.03	599	3.23	0.05	-0.02	1887	0.86	0.01	0.02	339	0.85	0.02	0.01

Note: Asterisks indicate t-test for equality of means. Differences in mean at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ levels. Equal variances are not assumed and tested by Levene's test for equality of means. Differences in the number of observations (N) within each category respond to missing responses.

Table 2.3: Multinomial logit analysis: Intrapreneurs, entrepreneurs, employees and engaged intrapreneurs

Independent variables	Intrapreneur vs. Entrepreneur (1)		Intrapreneur vs. Employee (2)		Intrapreneur vs. Engaged Intrapr. (3)	
lnIncome	0.60**	(0.13)	1.31	(0.25)	0.68*	(0.15)
Fear of failure	1.79*	(0.55)	1.16	(0.33)	1.55	(0.50)
Training business creation	2.34**	(0.90)	2.03**	(0.73)	2.02*	(0.80)
Graduate	1.03	(0.37)	0.60	(0.20)	0.75	(0.27)
Perceived start up skills	0.11***	(0.04)	1.03	(0.30)	0.11***	(0.04)
Opportunity recognition	0.08***	(0.04)	0.37*	(0.20)	0.12***	(0.07)
Control variables						
Male	1.35	(0.41)	1.27	(0.36)	0.99	(0.32)
Age	1.36**	(0.15)	1.18	(0.12)	1.30**	(0.15)
Age sq	1.00**	(0.00)	1.00	(0.00)	1.00**	(0.00)
Know entrepreneur	1.24	(0.38)	1.13	(0.32)	0.88	(0.28)
N = 1,760						
Chi sq. = 334.98						
Prob > chi sq. = 0.00						
Pseudo R sq. = 0.106						

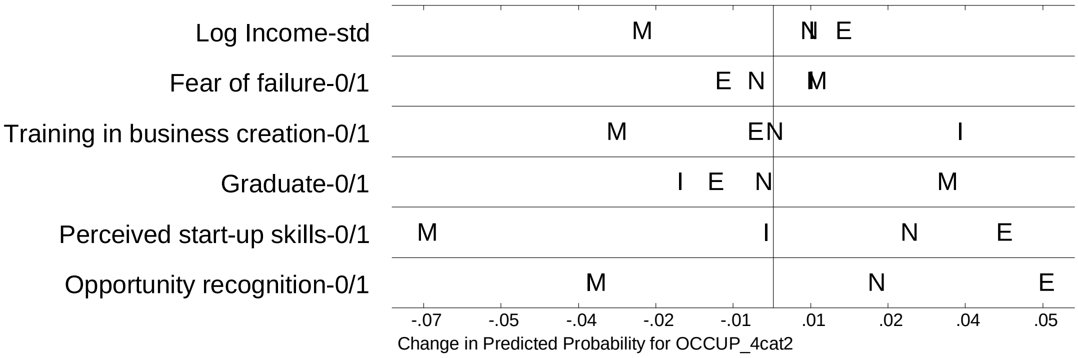
Note: Asterisks indicate significance level where * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Relative risk ratios from the multinomial logistic regression. Robust standard errors are reported in parentheses. In column 1 Entrepreneur is the base outcome. In column 2 Employee is the base outcome. In column 3 Engaged Intrapreneur is the base outcome.

Table 2.4: Multinomial logit analysis: Entrepreneurs and engaged intrapreneurs

Independent variables	Engaged Intrapreneur vs. Entrepreneur	
lnIncome	0.88	(0.11)
Fear of failure	1.15	(0.21)
Training business creation	1.15	(0.24)
Graduate	1.38*	(0.25)
Perceived start up skills	0.99	(0.29)
Opportunity recognition	0.66**	(0.12)
Control variables		
Male	1.35*	(0.23)
Age	1.04	(0.06)
Age sq	1.00	(0.00)
Know entrepreneur	1.42*	(0.27)
N = 1,760		
Chi sq.= 334.98		
Prob > chi sq. = 0.00		
Pseudo R sq. =0.106		

Note: Asterisks indicate significance level where * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Relative risk ratios from the multinomial logistic regression. Robust standard errors are reported in parentheses. Entrepreneur is the base outcome.

Figure 2.1: Discrete changes in predicted probabilities



Note: The graph shows changes in the predicted probabilities when the independent variable varies in one standard deviation for continuous variables, and from 0 to 1 for dummy variables. “E” refers to entrepreneurs, “I” to intrapreneurs, “N” to engaged intrapreneurs and “M” to employees.

Chapter 3

Mobility of Skills and Ideas

3.1 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 Marschke, 2005). This study 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% of the firms were founded by people who replicated or modified an idea encountered in their previous employment" (p.94). Recent data from the Global Entrepreneurship Monitor (2012) also shows that 50% of the nascent entrepreneurs that were previously or are still in paid-employment at the time of launching their firm develop an idea they found as part of their experience as an employee[1]. Many examples to illustrate the spawning activity of established firms are taken from Silicon Valley, Massachusetts, responding to the prominent spinoff ac-

[1]There is no difference in this fraction across countries in terms of their phase of economic development. The main differences lies in that the proportion of entrepreneurs that affirm having been in employment before setting up their business or being still in employment in addition to working on their own business is signicantly higher in innovation driven economies (85% versus 65% and 40% in efficiency- and factor-driven economies, respectively).

tivity 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 chapter, I introduce a new theory on spinoff formation that unravels this question and allows understanding the knowledge flows from incumbents to spinoffs. To do so, I extend Hvide (2009) to incorporate the influence of previous employer's size on determining the acquisition of skills. Although Hvide (2009) also focuses on the size of firm that entrepreneurs were previously working for, he emphasises the differences between small and large firm in acquiring information about the quality of the ideas generated within the firm. Managers in large organisations, as he argues, are worse at monitoring and therefore knowing the precise value of ideas, in contrast to managers in small firms who can observe their actual value. In the present study both small and large firms have the same access to information but I account for the differences in 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[2] as the measure of skills that are accumulated 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

[2]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 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.

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 positive association between firm size and expected growth of the firm, which is consistent with the prediction that the ideas implemented by employees coming from larger firms are on average of a higher quality. This is of particular interest, as it suggests that although balanced skills acquired in small firms may enhance their likelihood to move into 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 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, usually as the result of the identification criteria, although it is more specific than in the studies that examine entry into self-employment as a proxy for new business start-ups. 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 study 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 chapter.

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 study 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, 2009b; 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 (2009b) 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 chapter proceeds as follows. Section 3.2 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 3.3 introduces the data and provides the results of the empirical analysis. Finally section 3.4 concludes.

3.2 A Basic Model

I build a 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 works 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 pursuing 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 signalling 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 Q indivisible 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: $s = Q/n$ 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 ($t_i = 1/s = n/Q$). 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 $1/Q$ 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, $n > Q$, I consider that multiple workers are assigned to the same task and 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 the 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[3]. Becker and Murphy (1992) argue that there are other team (or firm) size determinants beyond the extent of the market, namely 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.

Workers' productivity is determined by their human capital, which is in turn comprised by their innate skills to perform the task and the knowledge acquired in the

[3]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).

labour market. Formally, human capital in period t is accumulated as:

$$K_t = \sum_{i=1}^{Q}(t_{it}t_{it-1} + t_{it}k_{i0}) \tag{3.1}$$

where $k_i^0 \in [0, 1]$ are innate skills to perform task i[4]. As in Gathmann and Schönberg (2010) the first term can be interpreted as the portable skills across occupations[5] and the second term as the quality of the match between worker's innate skills and those required in the chosen occupation. 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 ($K_1 = \sum_{i=1}^{Q} t_{i1}k_{i0}$). 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 rearranging with the human capital equation (3.1), I obtain

$$x\sum_{i=1}^{Q} t_{i2}t_{i1} + x\sum_{i=1}^{Q} t_{i2}k_{i0} - c \tag{3.2}$$

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 in 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

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

[5]The multiplicative form has been chosen over other forms, such the additive, to enable skills to accumulate only when the worker performs tasks he/she already performed the previous period (i.e. when both t_{i1} and t_{12} are nonzero.

skills. Taking an example to see this, consider the mentioned extreme case where workers in small firms have balanced skills and spend $1/Q$ of their available time in all Q 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 $1/Q$ of the time to perform all Q tasks. Now think of a worker in a small firm switching from paid employment into entrepreneurship. He transfers $(1/Q) \times (1/Q) = 1/Q^2$ of his task-specific skills in each task, which sums up to $1/Q$ (i.e. $\sum_{i=1}^{Q} 1/Q^2 = Q/Q^2 = 1/Q$), 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 $(1/Q) \times 1 = 1/Q$ 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.

Hence 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 important 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 knowledge about the many aspects of the business. This leads to the first empirical prediction:

P1: Workers from small companies undertake projects that are closer to the core business of their former employer when moving into entrepreneurship.

3.2.1 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:

$$w \geq x \sum_{i=1}^{Q} t_{i2} t_{i1} + x \sum_{i=1}^{Q} t_{i2} k_{i0} - c \tag{3.3}$$

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 (3.3), it yields a positive payoff to the employer $\alpha x - w = \alpha x - x \sum_{i=1}^{Q} t_{i2} t_{i1} - x \sum_{i=1}^{Q} t_{i2} k_{i0} + c > 0$[6] and shows that all ideas will be developed by incumbents and no spinoff will be formed.

[6] 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.

3.2.2 Asymmetric Information

Under the asymmetric information setting the worker observes x but the employer does not, instead the latter just knows its distribution, $f(x)$.[7] Following the approach by Hvide (2009) the employer's problem is to maximise the expected profits subject to workers' participation constraint (3.3), which rearranging yields $z = \frac{w+c}{\sum_{i=1}^{Q}(t_{i2}t_{i1}+t_{i2}k_{i0})}$. This gives:

$$\max_{z} \int_0^z (\alpha x - w) f(x) dx = \int_0^z (\alpha x - z\sum_{i=1}^{Q} t_{i2}t_{i1} - z\sum_{i=1}^{Q} t_{i2}k_{i0} + c) f(x) dx \qquad (3.4)$$

And the first order condition requires

$$\Pi_z^{'} = (\alpha z - z\sum_{i=1}^{Q} t_{i2}t_{i1} - z\sum_{i=1}^{Q} t_{i2}k_{i0} + c) f(z) - (\sum_{i=1}^{Q} t_{i2}t_{i1} + \sum_{i=1}^{Q} t_{i2}k_{i0}) F(z) = 0$$

Whenever the set of tasks in the first period is the same (or a subset) set of tasks in the second period the worker makes use of all the task-specific knowledge, then $\sum_{i=1}^{Q} t_{i2}t_{i1} = t_{i2}$ (since $\sum_{i=1}^{Q} t_{i2}t_{i1} = \sum_{i=1}^{Q}(n/Q) \times (n/Q) = Q \times n^2/Q^2 = 1/Q$)[8]. 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

$$\Pi_z^{'} = (\alpha z - z t_{i2} - z\sum_{i=1}^{Q} t_{i2}k_{i0} + c)\, f(z) - (t_{i2} + \sum_{i=1}^{Q} t_{i2}k_{i0})\, F(z) = 0$$

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,

[7] 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.

[8] Recall that tasks are indivisible, so after reducing the fraction n/Q to lowest terms the numerator becomes 1.

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 refers to the size of the firm that employees are working for in the first period, namely n_1, which as explained, determines the time allocated to each of the tasks in that period: $t_{i1} = n_1/Q$. Although it affects the human capital accumulation in the second period, it has no effect in the optimal quality level $z^*(\partial z^*/\partial n_1 = 0)$, 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 by n_2 (which will determine the span of tasks as well as the time employed for each of the tasks in period 2, i.e. $t_{i2} = n_2/Q$). Implicitly differentiating the first order condition and applying the chain rule with respect to the entrepreneurial team size it satisfies:

$$\begin{aligned}\frac{\partial z^*}{\partial n_2} &= -\frac{\partial^2\Pi/\partial z \partial t_{i2}}{\partial^2\Pi/\partial z^2}\frac{\partial t_{i2}}{\partial n_2} = -\frac{\partial z^*/\partial t_{i2}}{\partial^2\Pi/\partial z^2}\frac{\partial t_{i2}}{\partial n_2} \\ &= \frac{z^* f(z^*)(\sum k_{i0}+1) + F(z^*)(\sum k_{i0}+1)}{\partial^2\Pi/\partial z^2}\frac{1}{Q} < 0\end{aligned}$$

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[9].

Opportunity Costs Argument

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 signalling 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 ($w_1 = ... = w_Q$), wages in the second period, w^2, are given by

$$w^2 = wK_2 = w\sum_{i=1}^{Q} t_{i1}t_{i1} + w\sum_{i=1}^{Q} t_{i1}k_{i0} \tag{3.5}$$

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

$$x'(\sum_{i=1}^{Q} t_{i2}t_{i1} + \sum_{i=1}^{Q} t_{i2}k_{i0}) - c \geq w(\sum_{i=1}^{Q} t_{i1}t_{i1} + \sum_{i=1}^{Q} t_{i1}k_{i0})$$

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

$$x' \geq \frac{w(\sum t_{i1}t_{i1} + \sum t_{i1}k_{i0}) + c}{\sum t_{i2}t_{i1} + \sum t_{i2}k_{i0}} = \frac{w(t_{i1} + \sum t_{i1}k_{i0}) + c}{t_{i2} + \sum t_{i2}k_{i0}} \tag{3.6}$$

and the derivative with respect to the firm size yields

[9] 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.

$$\frac{\partial x'}{\partial n_1} = \frac{\partial z^*}{\partial t_1}\frac{\partial t_1}{\partial n_1} = \frac{w(1+\sum k_{i0})+c}{t_{i2}+\sum t_{i2}k_{i0}}\frac{1}{Q} > 0$$

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. Since becoming an entrepreneur requires performing a wider set of tasks, it implies that the expected return of the idea at which workers in these organisations are willing to reveal their discovery or quit the firm is higher and only those with ideas on the top range of the quality distribution will leave the firm[10].

The opportunity costs argument lead us therefore to the following predictions:

> P2: Large firms generate less spinoffs.
>
> P3: On average, spinoffs generated by employees coming from large firms outperform those coming from small firms.

Yet, although coming from a large firm has a negative effect on generating low quality spinoffs no significant difference should be expected for high quality projects, since employees from both small and large firms discover such ideas. Then:

> P4: Previous employer's size has no significant effect on the probability to create high quality spinoffs, yet large firms are negatively associated with low quality projects.

[10]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 more likely to become entrepreneurs afterwards. Remember that there are two rationales for wage growth in this model: it could be the result of human capital acquisition 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 the strongest skills. It is true that they will have a comparative advantage in 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, 2009b; Wagner, 2004) does not drive the decision to spinoff here. I return to this issue in the empirical section.

Figure 3.1 shows the three possible outcomes on a line that represents 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 larger the size of the firm (as well as higher start-up costs and wages per labour unit). This means that incumbents may miss valuable business ideas as a result of promoting skill premiums through a greater specialisation of labour as the means to increase productivity.

3.3 Empirical Analysis

3.3.1 Data

I use 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 data from the 2010 wave, when an extension to the standard questionnaire was made to collect information about the last employment of entrepreneurs and of those 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[11]. In practise, this accounts for businesses that have not paid salaries for

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

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%, 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[12]. 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 3.2 provides the mean and standard deviation of the set of relevant variables for entrepreneurs and employees separately (for a detailed description of variables see table 3.1). 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.

3.3.2 Analysis

I organise the empirical evidence in two parts. I start by studying the effect of last employer's size on the likelihood to move into entrepreneurship (P2) and the propensity to enter the same industry that the parent firm operates (P1), as a way to assess how closely spinoffs are related to parent firm's core business. In the following subsection I examine performance differences based on last employer's size to test predictions P3

[12]Precisely, 25% 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.

and P4.

Transitions into Entrepreneurship

As said, 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 table 3.1 for a more detailed description of the variables). For most models I compare the continuous and categorical forms of the business size, which allows assessing whether the effect is monotonic. Given that the data on firm size is highly skewed, I follow the winsor technique and truncate the values at the 99th 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[13].

Table 3.3 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. Recall that the theory predicts that large firms are negatively associated with transitions into entrepreneurship (P2). Consistent with this prediction, the results indicate a negative effect of firm size, but statistically insignificant. Conversely, 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% 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). This serves to test P1, namely that entrepreneurs coming from small firms are more likely to set up businesses within the same industry they last worked in, presumably because they transfer a wider set of knowledge. I create a new variable measuring the degree of relatedness between the two industries by looking at their primary International Standard Industrial Classification (ISIC) four-digit codes provided in the dataset[14]. I define intra-industry

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

[14] Respondents were not asked about the specific ISIC code but the kind of activity his employer

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 enough proximity of industries. The results are shown in table 3.4. They support (columns 1 and 2) the theoretical prediction, P1, that the smaller the firm the more likely entrepreneurs are 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 on being an entrepreneur. Saying in another way, decreasing the previous employer's business size by one percent is associated with a 3.6% increase of the predicted probably of entering the same industry (22.3%) 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[15] (j) and subtract it from one (Aghion et al. 2005, p. 704-5):

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

engages in or the way it would be listed in a business directory. Of course, this ignores secondary or further industries they also operate in.

[15]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.

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 *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 the (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 with 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 in 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 3.3). 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 on average, the spinoffs coming from large companies outperform those coming from small firms (P3), since employees in large firms are less likely to engage in low quality projects due to higher opportunity costs associated with their returns to specialisation. Yet, we should expect both small and large firms to generate high quality spinoffs (P4). 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, the dataset does not provide information on the actual performance of the businesses. However, it provides data on 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.

I start by estimating quantile regression models to better understand the underlying mechanisms in the entire distribution of firm growth expectations. Table 3.5 reports the 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.

Consistent to the empirical prediction P3 the effect of firm size is negatively associated with projects with lowest growth expectations, but the effect is statically insignificant. It is not until the upper quartile (q=.75) when the effect of firm size turns significant. Here, a percentage point increase in the firm size increases the expected number of employees in 16.5% 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 3.6. So this somehow contradicts the prediction P4 that entrepreneurs coming from both small and large firms equally engage in high quality projects.

Both in table 3.6 and figure 3.2 I compare the quantile regression estimates with the OLS coefficient. This permits to see the effect of previous employer's size on the average expected growth of firms, compared to firm size effect across the entire distribution. As the first column in table 3.6 shows the OLS estimate is, as predicted by P3, posively related to firm growth, although it is insignificant. As seen earlier, the quantile regression estimates suggest a positive effect of firm size over most of the range of the distribution and reflect a larger firm size effect than the OLS estimate (indicated with the horizontal dotted line in figure 3.2) over around q=.4. In fact, the quantile estimate increases sharply at 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 results indicate that the best ideas are implemented by workers coming from larger firms and suggest that contrary to my predictions employees from large firms are either more likely to discover high quality ideas or their employment experience allows them to acquire valuable skills to succeed in entrepreneurship.

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, 2009b) 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 (3.2), which measures the quality of the match between the innate skills and the required skills in the occupation and has been ignored till 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, 2011). As it has been already shown in table 3.3 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 [16]. 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 it requires tracking individuals over their employment histories which is not feasible here. Hence, 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[17]. 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 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 coun-

[16] Results are available upon request.

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

ties, 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 3.7. 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 to the logit coefficients[18]) and the IV probit estimates in columns 3-4 and 7-8. I find that the effect of the previous employer's size is stronger, both in magnitude and significance, when I instrument for this measure and consider entries within the same industry. Yet, although the coefficient for the IV specification is bigger when estimating the likelihood of becoming an entrepreneur, the effect is still 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 transitions into entrepreneurship.

3.4 Conclusions

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 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

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

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.

Finally, a number of caveats need to be noted regarding the present study. The theoretical predictions rest on the assumption about the higher division of labour in larger firms but ignores the position of the workers within the organisation. This may seem quite unrealistic if we think, for example, about a manager in a large company, who will need to understand many different aspects of the business and according to my model is supposed to be a specialist. Given that I noticed the limitation when the data from 2010 was already collected I am unable to control for the position in the company using the present dataset. New data from 2011 will however contain information about the position or the worker as well as additional information about the internal organisation of the company that I plan to incorporate as an extention of this study. Likewise, pooling data from 2010 and 2011 will allow me to increase the sample size, which is still relatively modest when I look at transitions among individual entrepreneurs or examine growth prospects. Although I have tried to correct for outliers, which could have easily distorted the results, a larger sample would have definitely strengthen the robustness of my results.

Figure 3.1: Decision of workers

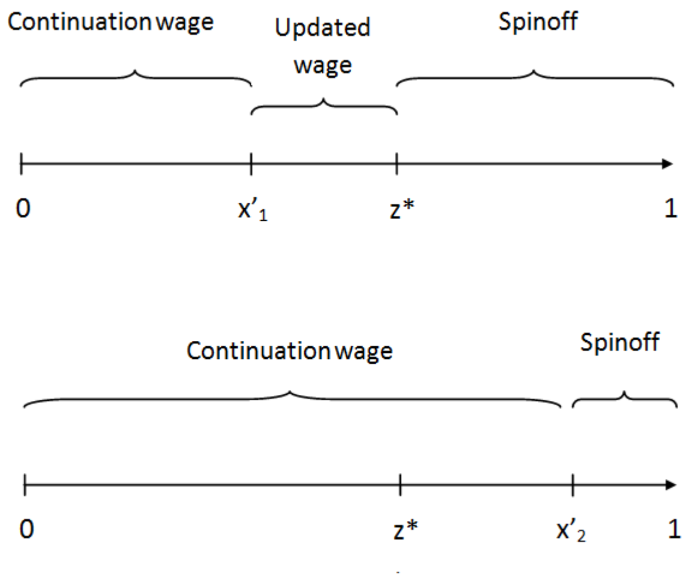


Table 3.1: Description of variables

	Variables	Description
1	Log firm size	Number of employees working for the (current or more recent) employer in natural logarithms.
2	Private	Dummy taking 1 if the most recent 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 most recent 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 have been last working for.

Table 3.2: Descriptive statistics of employees and entrepreneurs

	Employees		Entrepreneurs		
	Mean	SE	Mean	SE	Diff.
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 which 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 3.3: Transitions 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 of logit regressions where the dependent variable takes 1 if engaged in entrepreneurship; Robust standard errors in parentheses.
Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.4: Transitions into entrepreneurship in the same industry: Intra-industry spinoffs

	All				Only entrepreneurs			
	(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 business	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 of logit regressions where the dependent variable takes 1 if individual sets up a firm in the same industry he/she last worked in; Robust standard errors in parentheses.

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

Table 3.5: 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	
Industry	No		No		Yes		Yes	

Note: Standard errors in parentheses. The dependent variable is the logarithm of expected number of employees in 5 years time. 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.

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

Table 3.6: Expected growth in 5 years. Comparison of OLS and .75 quantile coefficients

	OLS	QR_75	QRb_75	CQR_75
	(1)	(2)	(3)	(4)
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

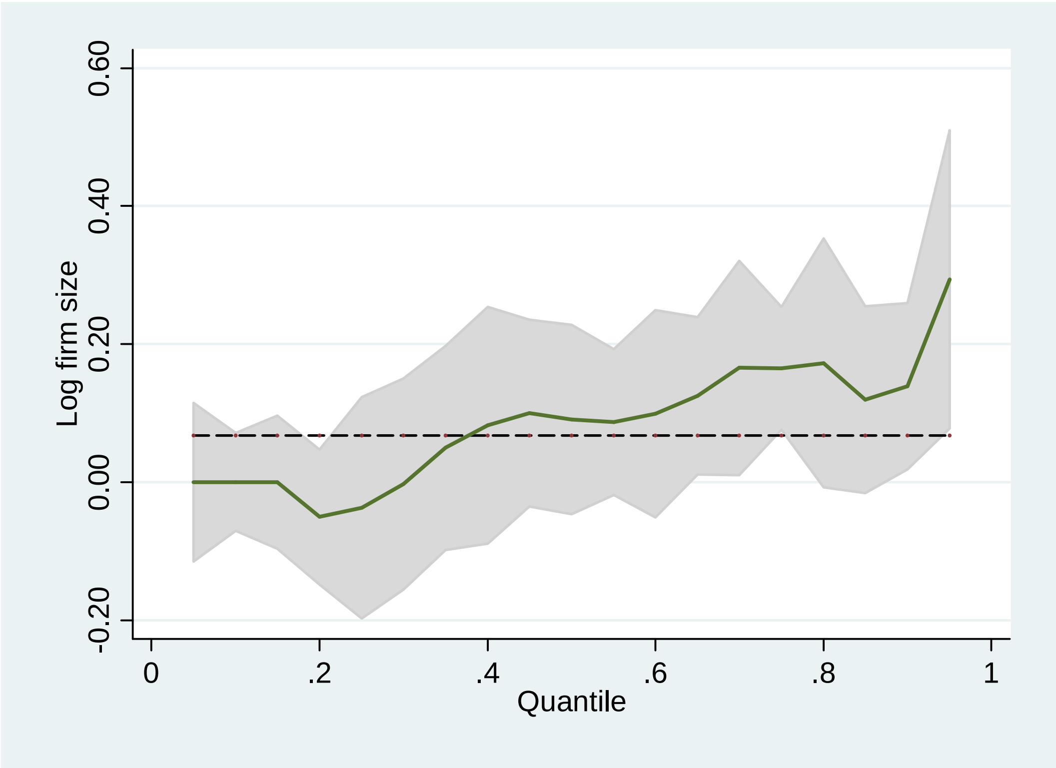
Note: Standard errors in parentheses. Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the logarithm of expected number of employees in 5 years time. The table reports (1) OLS, (2) quantile regression, (3) quantile regression with bootstrapped standard errors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

Table 3.7: Transitions into entrepreneurship and entry in the same industry. IV estimates

Transition into entrepreneurship	2sls	liml	ivprobit	probit
	(1)	(2)	(3)	(4)
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	2sls	liml	ivprobit	probit
	(5)	(6)	(7)	(8)
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: Comparison of coefficients estimated by 2SLS, LIML, IV probit and probit models. 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. Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 3.2: Expected growth. Quantile regression



Note: The figure shows the quantile regression estimates along with the OLS coefficient of previous employer's firm size on expected 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.

Chapter 4

Changing Labour Market Conditions: Employee Mobility and Entrepreneurship

4.1 Introduction

A well documented empirical regularity regarding transitions into entrepreneurship is that the vast majority of entrepreneurs come from a position of an employee in small firms, which has been referred to as the small firm (size) effect in the literature (Sorensen, 2007; Wagner, 2004; Parker, 2009b; Elfenbein *et al.*, 2010; Hyytinen and Maliranta, 2008). This study examines whether the inverse statistical association between the last employer's firm size and the propensity of entrepreneurial entry[1] stems from an underlying employment dynamic and, indeed, whether it varies over the economic cycle. Given that moves into entrepreneurship are a particular case of the general processes of labour market dynamics, I analyse employee mobility decisions along with moves into self-employment using a matched employee-employer panel data from Spain for the period 2005-2010. This period is of particular interest as it coincides with the sharp overall rise in unemployment during the latest recession as well as an increasing dispersion in unemployment across regions, which provides an opportunity to identify

[1] In this chapter, and in contrast to earlier chapters, I examine individuals moving into self-employment rather than new business founders.

the effect of unemployment on employee decisions to move into self-employment.

The explanations for a greater flow of employees moving into entrepreneurship from small firms have so far ignored the cause of separation. In fact, most theories on spinoff formation rely on the assumption that employees quit the incumbent firm to develop the idea on their own (see Klepper (2001) and Klepper (2009) for a review). Yet the decision to change jobs, and equally the decision to enter entrepreneurship, may be related to the reason to terminate the employment contract and the labour market conditions at that point in time. While some entrepreneurs will voluntarily leave their current employer to engage in entrepreneurship others will do so following a dismissal. Hence, we cannot fully understand the impact of previous working experiences on the decision to move into entrepreneurship without considering that state at which individuals make the decision. Whether the observed firm size effect should be attributed to the causes of employee turnover is analysed by making use of the information on the reasons why an employee leaves their job. The empirical identification relies on the rapidly changing labour market conditions in Spain, which are expected to increase the flow of dismissed workers and alter the incentives to become an entrepreneur. Individuals are expected to prefer working on their own account whenever the expected benefits from it, both monetary and non-monetary, are higher than those in paid-employment (Harrison and Hart, 1983; von Greiff, 2009). Hence, while dismissals reduce the opportunity costs of self-employment by lowering alternative earnings from waged-work and make self-employment a more attractive option, negative economic prospects may also limit the availability of profitable business opportunities.

I find support for the existence of the small firm size effect, which persists after controlling for the reason why an individual leaves their current employer. The effect of dismissals turns out to be a key driver in the move into self-employment and it is found to exert a larger impact the smaller the firm workers are dismissed from. I claim that this could be partly explained by the higher probability to be dismissed from small firms, which is also reflected in a higher probability of turnover among workers in small firms like the literature also suggests (Oi and Idson, 1999). In fact, when I examine the probability of entry into self-employment conditioning on mobility, as a means to isolate self-employment entry factors from the ones that determine turnover decisions, the results show that dismissed workers are less likely than those who leave voluntarily to choose self-employment over paid-employment when they come from large firms.

These results shed light on the strand of research which examines the impact of unemployment on entrepreneurial entry. In contrast to the approach of many earlier studies that analyse its effect on aggregate measures of self-employment, I am able to examine micro-level changes in the underlying flows of workers across firms and into self-employment caused by, in this case, a depressed labour market climate. I find a substantial and stable negative effect of unemployment on employee turnover and self-employment entry probabilities. Moreover, the observed small firm effect seems to be intensified during adverse labour market conditions. Taken together, the results suggest that the increasing small firm effect over the recession might be driven by a greater share of dismissed workers from small firms engaging in self-employment and conversely, less workers from large firms leaving voluntarily the job to start working in their own account.

The small firm effect has been widely interpreted as evidence that small firms provide better training to their employees to set up their own business afterwards. Yet it could be the case that higher opportunity costs associated with higher average salaries and more opportunities for promotion in large firms discourage workers from leaving their jobs to enter self-employment. Therefore, we may observe more self-employed coming from small firms but for reasons other than learning or skill acquisition processes (Elfenbein *et al.*, 2010). Thus, my approach towards ruling out this possibility is to examine only those who are unemployed. I create a new dataset of unemployment benefit recipients and examine the process of entry into self-employment given the size of the firm they were dismissed from. Once again, I find that those who were dismissed from a small firm are more likely to become self-employed, which reverses when analysing re-employment in a new wage job. The negative effect of unemployment also holds, meaning that the probability to become self-employed declines with unemployment. This supports the earlier result on the dominant disincentive effect of unemployment over the potential push mechanism caused by the lack of alternative jobs in paid-employment. Finally, I investigate the link between the size of the last employer and entry into self-employment solely within the same industry in an attempt to identify the actual effects of the working experience and workplace characteristics, which are expected to exert greater effect when flows between one employer into self-employment occur within the same industry. I find that the small firm effect is substantially larger for entries in the same industry. I interpret this finding as indicating that working experiences actually shape entrepreneurial intentions and skills of prospective entrepreneurs, hence the greater flow of entrepreneurs coming from small firms cannot be entirely attributed to sorting processes.

The empirical work is based on data from "Muestra Continua de Vidas Laborales" (MCVL) or the Longitudinal Sample of Working Lives, which is a random sample of the Spanish Social Security records crossed with Income Tax data and population census. From the raw data, I construct an employer-employee dataset covering the period 2005 to 2010 representing the career histories of about 4% of all individuals having any relationship with the Spanish Social Security. Here, I can identify the self-employed as those who contribute to the system through the special account for the self-employed.

The rest of the chapter proceeds as follows. The next section sets out the related literature that motivates this study. Section 4.3 presents an overview of the Spanish labour market institutions in order to set the context for the study as some of its peculiarities become crucial to understand the interpretation of the empirical results. Section 4.4 explains the empirical strategy, which includes a discussion of the main econometric model used. Section 4.5 presents the data and descriptive analysis. Section 4.6 reports the main results and section 4.7 concludes.

4.2 Related Literature

The present work is closely related to two strands in the literature. Firstly, it builds on recent studies that analyse how workplace characteristic affect the move into entrepreneurship. Until recently, much of the literature that has examined the individual decision to become an entrepreneur has focused on studying innate traits, such as attitudes and preferences, and issues related to the access to the required start-up capital which are conditioned by household earnings and wealth. When references were made to contextual factors, these were typically related to the family background and the transmission of job values from entrepreneurs to their children (Dunn and Holtz-Eakin, 2000; Kawaguchi, 2003; Halaby, 2003). If one thinks about entrepreneurship as an occupational choice, however, employment histories of the individual can no longer be neglected. The view that career backgrounds and working environments influence entrepreneurial intentions and subsequent performance of businesses has been supported by an increasing number of studies which find that the majority of entrepreneurs were in paid-employment before starting their own businesses (Sorensen and Fassiotto, 2011). Indeed, a significant fraction of entrepreneurs are found to develop a business idea which they had encountered in the workplace (Bhide, 2000; Cooper, 1985). This has served to motivate studies on the knowledge flows that occur through the formation of spinoffs and the causes that hinder incumbents from pursuing the ideas generated within the organisation (Klepper, 2009). The idea that firms differ in the access to knowledge and learning opportunities they provide to employees would explain why better performing firms, in terms of longevity, market share or degree of technological innovativeness, and large firms spawn more and best performing spinoffs (Gompers *et al.*, 2005; Klepper and Thompson, 2009; Klepper, 2009; Agarwal *et al.*, 2004). Employees working in these firms would be able to acquire superior knowledge and learn from successful entrepreneurs, therefore, be more likely to quit and apply this knowledge by starting their own business in the same industry (Burton *et al.*, 2002; Klepper, 2009; Agarwal *et al.*, 2004; Gompers *et al.*, 2005; Chatterji, 2009). These regularities have been well documented in infant and growing industries, such as disk-drives, automobile, semiconductors, lasers or medical devices (Klepper, 2001, 2009).

This contradicts the prevailing view in non-industry specific studies which state that most workers switch to entrepreneurship from a job in a small firm (Wagner, 2004; Parker, 2009b; Elfenbein *et al.*, 2010; Hyytinen and Maliranta, 2008). These studies posit that workers are exposed to a better entrepreneurial training ground in small firms, where they are assigned multiple tasks and acquire balanced skills which are necessary in the setting up of a new venture (Lazear, 2004, 2005). Because of a lower degree of division of labour in small firms workers get involved in many different activities and get the opportunity to understand the key aspects of the market and the business which may prepare them for future business ownership. This can also facilitate the identification of business opportunities in the market, especially those related to the core activity of the incumbent and within the same industry. Moreover, potential or latent entrepreneurs have knowledge of networks (of suppliers, clients or successful entrepreneurs, for example) and resources that will enable them to found their own business. Apart from being better equipped to form a new firm through the duties they perform, by interacting with successful entrepreneurs workers in small firms are likely to adopt positive attitudes towards entrepreneurship and consequently, be more willing to pursue the opportunities on their own (Nanda and Sorensen, 2010). One could also argue, in contrast, that the position or role at work (Lazear, 2004, 2005) indirectly determines the scope of his/her learning irrespective of the size of the firm. Someone working at higher levels in a large organisation, who is for example responsible for a division, will have better knowledge of the critical resources and information (Rajan and Zingales, 2001) and will know the main strategic decisions of the business despite the scope of tasks being narrowly defined at the firm level.

An alternative argument to this view on the shaping of skills and attitudes while working in small firms, which could be easily extended to the above mentioned advantages of working in successful firms, stresses the self-selection of workers in firms of different size based on their abilities, both innate and acquired, and lifestyle preferences. Based on the same logic that workers with balanced skills have advantages to perform the multiple tasks that launching a business entails, individuals with innate balanced abilities will also tend to join small firms in the first place as a result of a better expected match. Similarly, individuals with preferences for autonomy and lower risk aversion will be attracted by jobs in small firms, where unexpected changes and higher volatility of wages are more likely to occur and given the less formalisation of activities, greater flexibility and autonomy to make decision may be permitted at lower levels of the organisation (Parker, 2009b; Sorensen, 2007; Elfenbein *et al.*, 2010; Dunne *et al.*, 1989). Thus, by exactly the same sorting mechanism, workers in small firms will be more attracted to entrepreneurship throughout their employment career, regardless of workplace characteristics yielding any influence, which could explain the higher flow of individuals from small firms to entrepreneurship. The main difficulty in empirical works relies on isolating this sorting effect from treatment effects, understood as the actual influence of the workplace in shaping entrepreneurial skills and mindset. My approach here is to use the fixed-effects specification in panel regressions to control for the unobserved heterogeneity of individuals, which as far as I am aware, has never been applied in this context before. Because the identification is based on within individual changes of those who actually become entrepreneurs, it requires using a dataset on a large number of individuals, as well as a sufficient number of observations on each individual over time.

Moreover, this study aims to place the firm size effect in perspective by analysing the reasons why an individual leaves a particular firm – as a result of dismissal or voluntarily to take up a position in another firm or to become self-employed. The great majority of theories explaining the spinoff formation rely on the assumption that employees leave the firm to develop the idea on their own, both when the departure is motivated by the refusal of the employer to pursue the idea or it is driven by the unilateral decision of the worker to fulfil his/her career or lifestyle goals. In either case, the termination of the employment relationship is always assumed to be initiated voluntarily by the employee. This neglects the fact that in practice the termination of the contract can occur as a result of employee dismissals. The distinction between resigning and being dismissed is well recognised in the turnover literature, which focuses on the determinants of job change but it rarely considers entry into entrepreneurship or self-employment. Among the few papers that look at this relationship, Farber (1999a) provides evidence that displaced workers, referring to involuntary separations based on a decline in job requirements in the firm, have more difficulties in finding regular jobs, hence they are more likely to be re-employed in temporary and part-time jobs but are less likely to set up small businesses. However, there is no difference between job losers and non-job losers in their propensity to become solo entrepreneurs. It is intuitive to think, however, that dismissed workers may have greater incentives to become self-employed given their lower reservation wage after the separation. This may relate to the fact that dismissed workers lose the return on their specific human capital they acquired in the firm, which does not have any value when being re-employed by a new firm (Farber, 1999b). This is supported by the findings of von Greiff (2009), Moore and Mueller (2002) and Fairlie and Krashinsky (2012) on the greater probability of self-employment after a displacement, in particular among low-income earners workers and those worse placed in the labour market, such as older workers or immigrants who may have less options in the wage sector. Turning to the firm size effect, and if we think in terms of opportunity costs, we could expect workers in larger firms to be more reluctant to resign and launch a new venture because, on average, they earn higher wages, especially the longer they have worked in the firm (Oi and Idson, 1999). This is consistent with the negative relationship of turnover propensity on firm size. While dismissals remove the differences in the opportunity costs that are likely to be associated with less moves from large firms into self-employment, selection and treatment effects would both still predict higher flows of individuals losing their jobs from small firms to self-employment.

The size of self-employment inflows by those workers who leave voluntarily the firm and those that are dismissed are expected to adjust differently to the economic cycle. As the economy slows, an increasing scale of job destruction could lead the group of dismissed workers to dominate entries into self-employment and also because an unfavourable economic climate will discourage employees to leave their employers voluntarily. This implies that if employees from small and large firms are differently affected by the processes of job destruction and exhibit different responses to the incentives to switch to entrepreneurship, for example, because of their expected wages in an alternative job, then the effect of firm size will differ over the economic cycle. Thus, I examine the extent to which the small firm effect may stem from labour market conditions, and, in particular, how the firm size effect evolves as economic conditions worsen in the context of the latest recession in Spain. By doing so, I also attempt to help reconcile the contradictory findings of the firm size effect in industry specific and general labour market studies.

Second, this study also contributes to the stream of research on the influence of unemployment on self-employment entry. Although this relationship has raised the interest of researches for decades, to date, the findings have been mixed and inconclusive. Two main sets of factors have been claimed to operate simultaneously. One set of explanations has identified "push" factors as a driver of higher self-employment entry rates during depressed economic conditions (Niittykangas and Tervo, 2005; von Greiff, 2009; Evans and Leighton, 1990; Schuetze, 2000; Harrison and Hart, 1983; Thurik *et al.*, 2008)[2]. When alternative paid-employment options are scarce, the opportunity costs of self-employment falls, hence dismissed workers and new entrants in the labour market tend to be more prone to engage in entrepreneurship. For many of them, in fact, self-employment represents the second-best solution (Henrekson, 2007), meaning that if they were able to obtain a regular job that enabled them to earn their living they would not become self-employed. A second set of explanations, described as "pull" factors, argue that the economy acts procyclically with flows into entrepreneurship during prosperous times increasing while during adverse economic conditions the number of employees leaving their jobs voluntarily to enter self-employment decreases, (Meager, 1992; Carrasco, 1999; Reynolds *et al.*, 1994; Blanchflower and Oswald, 1998). This occurs because as the economy grows and demand rises more profitable business opportunities arise. Moreover, favourable economic conditions tend to increase the disposable income of households, which can be invested in the setting up of a business (Hurst and Lusardi, 2004). Yet, the empirical evidence offers contradictory findings when these two sets of factors are examined. As Storey (1991) and more recently Congregado *et al.* (forthcoming) suggest most micro-economic studies find support for the pull hypothesis, while macro-economic studies point to an ambiguous or weak positive association between the 'push' of unemployment and self-employment. The macro-economic studies are more numerous, partly because micro data has not become available until recently and the research on the cyclical aspects of entrepreneurship was quite prolific during the 80s and early 90s.

[2]The study by Harrison and Hart (1983) differs from the others in that they examine new business registrations rather than transitions into self-employment.

Further, the comparison between *micro* and *macro* studies is often problematic because the former mostly focus on the individual decision-making process to enter self-employment, whereas many macro level studies take self-employment rates as the dependent variable. So the latter accounts not only for the flows into self-employment but also for the exits, the net result depending on the magnitude of the flows. Hence, as pointed out by Meager (1992), studying the stock or rates of self-employment may lead to spurious relationships between the economic cycle and self-employment, as outflows from self-employment are correlated with lagged inflows into it[3]. In this line of reasoning Thurik *et al.* (2008) show that the effect of unemployment on self-employment, and even the reversed effect of self-employment on unemployment, is long and therefore, it requires incorporating different and variable time lags. But even when restricting the attention to time series studies that only refer to inflows, among others by Harrison and Hart (1983) and Reynolds *et al.* (1994), differences in the findings persist.

4.3 Labour Market Institutions in Spain

Before turning to the empirical analysis I provide a brief overview of the Spanish labour market institutions, as some of its peculiarities will arise in the empirical results. Spain is the OECD country that has experienced the largest loss in employment during the latest recession; each percentage point fall in GDP has inflicted a 2.26 points increase in unemployment, well above other EU countries like the UK with a 0.46 percentage point increase or France, which shares more similar employment protection legislation, with a slightly larger 0.77 (Gregg and Wadsworth, 2010). The unemployment rate before the crises was, however, at similar levels, around 8%, and has soared to 20% in four years since 2008. This high responsiveness to the economic cycle is not unprecedented in Spain, as the labour market performed similarly in past recessions of the 1980s and 1990s and it is due, at least in part, to its labour market institutions and in particular, to the wide use of temporary contracts.

[3]Moreover, if self-employment is less responsive to economic cycles than the number of individuals in paid-employment, we would observe a rise in the self-employment rate during times of higher unemployment simply driven by a fall in the denominator.

Temporary or fixed-term contracts were allowed for regular activities in the mid-1980s to provide higher flexibility to the rigid employment protection regulation inherited from Franco's regime and as a way of reducing the 21% unemployment at that time (Dolado *et al.*, 2002). Until then, temporary contracts were only allowed in activities that were seasonal by nature such as many in agriculture or in the tourist industry. These new temporary contracts dramatically reduced the severance payments from 45 days' wages per year worked with a maximum of 42 month's wages[4] to 12 days' wages under the new temporary contracts. They had a maximum length of 3 years upon which they had to be converted into permanent (or open-ended) contracts or else terminated. Temporary contracts rapidly became widely used and peaked 35% of all contracts in the economy and 90% of the new contracts by early 1990s (Bentolila *et al.*, 2008; Petrongolo and Pissarides, 2008). A series of reforms (in 1994, 1997, 2002 and 2006) have subsequently tried to reverse this trend but failed to achieve lower than a 30% temporary employment share, double the EU average, until the beginning of the current crises, when the destruction of temporary jobs has increased the share of permanent workers in total employment. The Spanish labour market has been, therefore, renowned for its dualism or two-tier employment protection legislation where the insiders, holding a permanent contract, have maintained the initial strong security privileges and outsiders, workers with temporary contracts and unemployed, have low firing costs or no costs at all.

Volatility of employment is one of the most important implications of the high incidence of temporary contracts and the divide in dismissal costs. While temporary contracts allow higher hiring rates, adjustments during adverse market conditions come through a high destruction of temporary contracts. Costain *et al.* (2010) estimate that unemployment fluctuates between 21% and 33% more in the current dual market system than what it would in a setting with a single contract. The rationale for this lies on the fact that during expansions a fraction of temporary contracts has a productivity below the firing threshold in recessions. This implies that as soon as

[4] To be more precise, severance payments depended on the reason to terminate the contract. If there was an objective reason or applicable economic, organisational, technological or productive causes a lower severance pay of 20 days' wage for each year of seniority with a maximum of 12 month's wage was paid. In order to dismiss under the latter causes, however, administrative approval was necessary.

the economy slows these contracts are destroyed and cause accentuated employment losses. The authors argue that this is the main cause of employment fluctuations in dual contract labour markets. Given that permanent contracts are never created below the mentioned productivity threshold or margin, because of the anticipated firing costs, they are less responsive to economic cycles. So, as the authors argue, a context with a single contract with firing costs would behave similar to a scenario with only permanent contracts. The low conversion of temporary contracts into permanent ones suggests that the former serve as an instrument to increase flexibility to firms, in particular for those workers who perform low-skill activities and as a screening device for qualified candidates whose productivity is, *ex-ante*, unknown for the employer (Güell and Petrongolo, 2007). This is reflected in more frequent conversion rates at the time of the legal limit of temporary contracts especially among unskilled workers. Conversely, earlier conversions are more likely to occur whenever workers' outside options are higher and workers can credibly threaten to resign. The existing high turnover of workers consequently discourages employers from investing in human capital and providing training to temporary workers, as well as undermining employees' incentives to exert greater effort because of their lack of prospects for stability and promotion. This seems to partly explain the slowdown in the productivity of Spanish firms. Dolado *et al.* (2011) find that about 20% of total factor productivity growth slowdown in manufacturing between 1992 and 2005 is attributable to the fall in the conversion rate. Indeed, while temporary contracts are supposed to lead to permanent contracts, in practice many workers, particularly the youngest ones, get trapped in a sequence of temporary contracts and spells of unemployment spells.

Another aspect of the Spanish labour market is the high persistence of regional relative unemployment, defined as the deviations of regional rates from the national mean (Jimeno and Bentolila, 1998). This is by the way, together with the unemployment rise over the recession, the source of empirical identification in this paper. The ranking of regions and provinces (which correspond to the 50 NUTS III[5] regions in Spain) based on their unemployment rate has remained stable over the last three decades with a gap

[5]NUTS III corresponds to the level three of the Nomenclature of Territorial Units for Statistics (NUTS) of Eurostat. Given that most commuting occurs within provinces I assume that they constitute integrated labour markets.

of about 14 percentage points between the two extremes of the distribution. They have, however, evolved into forming two peaks in the distribution, consisting of a group of regions with relatively low unemployment and a larger group with higher unemployment rates (Bande *et al.*, 2008; Bande and Karanassou, 2010). Jimeno and Bentolila (1998) find that the persistence of regional differences in unemployment is a consequence of low inter-regional mobility and low responsiveness of labour participation to real wages and unemployment. Although Spain experienced high regional mobility flows until the early 1980s, much of the migration flows occurring from the countryside to the city in the 1950s and 1960s, these declined afterwards. Housing prices and unemployment benefits became more important in migration decisions, instead of unemployment and wage levels like in previous decades (Antolin and Bover, 1997; Jimeno and Bentolila, 1998; De la Roca, 2011). New inter-regional migrants are now predominantly skilled and most productive workers moving from low density urban areas to larger cities. Thus, migration has hardly helped to reduce differences in regional unemployment rates and the latest recession has even intensified the divergence across regions, as it will be shown in the next section.

In sum, the Spanish labour market is characterised by the coexistence of temporary and permanent contracts and the existence of regional differences in unemployment rates, which have been persistent over decades and even increased recently. These peculiarities serve as the basis of the empirical identification in this work, as the next section addresses.

4.4 Empirical Strategy

4.4.1 Identification

Spain constitutes a good case to understand the effect of unemployment on employment mobility due to the rapid rise in unemployment in the latest recession. The source of empirical identification comes from changes in unemployment over the years preceding the crises and during the recession. In particular, I use province level quarterly unemployment data, which provides the greatest variation. Figure 4.2 shows the province level (NUTS III) unemployment rates from 2005 to 2010, the studied period here, which illustrates the steep rise in unemployment from mid-2007 onwards. As mentioned earlier, there are persistent and increasing regional differences in unemployment over time, reflected by a wider dispersion around the median and larger spread of data beyond the first and third quartiles in the second part of the graph. By looking at both extremes of the distribution, the unemployment rate ranges from 4.06 (Huesca) to 13.67 (Córdoba) percent before the start of its rise, i.e. mid 2007, and from 7.8 (Gipuzkoa) to 31.68 (Las Palmas) percent at the end of 2010.

The geographical dispersion of unemployment for data in in the last quarter of 2010 is shown in figure 4.1. The provinces with highest unemployment rates in 2010 are mainly located in South Spain and the Mediterranean coast, which coincides with the regions whose growth have been largely dependent on the construction sector, hence suffered a larger decline in employment following the bursting of the housing bubble. In contrast, provinces with lowest unemployment rates are located in the North of Spain and the Ebro axis. Within country variation is obviously appealing from the statistical point of view, especially because there is no institutional and less cultural variation across regions than what it would emerge in a cross-country setting. So the study exploits both sources of variation: changes over time and within country differences.

4.4.2 Empirical Specification

Although transitions into different occupations occur in continuously, given the interest in measuring the effect of unemployment the estimation is performed using single and competing discrete-time hazard models, as they allow time-varying covariates to be incorporated. This requires reorganising the dataset to obtain a data row for each individual per interval of time at risk of transition, in this case defined in quarters of each year (on February 10, May 20, August 10, and November 10). Thus, the dependent variable measures the self-employment entry hazard (or either turnover or reemployment hazards), the probability of becoming self-employed in the interval $(t_{a-1}, t_a]$ conditional on not having done so until the end of the previous quarter and it is defined as: :

$$h_{it_a} = Pr[t_{a-1} \leq T_i \leq t_a | T_i \geq t_{a-1}; X_{it}] = F(\gamma + \beta' X_{it})$$

where X_{it} is a vector of time-varying[6] and constant set of covariates for individual i in time period t and T_i is a discrete random variable indicating the job spell end time. Since intervals are of equal length, h_{it_a} can be simply replaced by h_{ik} where k indexes quarters from $k = 1, ..., j$. The probability of surviving until the end of the quarter prior to the move is the product of not moving in each of the preceding intervals: $\prod_{k=1}^{j}(1 - h_{ik})$. Then, the likelihood contribution of the whole sample is the sum of the contributions of N individuals:

$$L = \prod_{i=1}^{N} \left[\Big(\frac{h_{ij}}{1 - h_{ij}}\Big)^{c_i} \prod_{k=1}^{j} (1 - h_{ik}) \right]$$

where c_i is a censoring indicator that equals 1 if the spell is complete and zero otherwise. Now we can adapt the censoring indicator, d_{ik}, to reflect whether the transition takes place in a given quarter, and zero otherwise. So if a person becomes self-employed, all periods before the quarter prior to the transition are treated as censored. Hence, the log-likelihood can be simplified:

$$\begin{aligned} logL &= \sum_{i=1}^{N} \sum_{k=1}^{j} d_{ik} \, log \Big(\frac{h_{ik}}{1 - h_{ik}}\Big) + \sum_{i=1}^{N} \sum_{k=1}^{j} log\,(1 - h_{ik}) \\ &= \sum_{i=1}^{N} \sum_{k=1}^{j} [d_{ik} \, log \, h_{ik} + (1 - d_{ik}) \, log\,(1 - h_{ik})] \end{aligned}$$

And this has the same form as the standard binary dependent variable model (Jenkins, 1995; Allison, 1982). The final step is to define the distribution of the hazard rate, h_{ik}. As there is no theoretical reason to expect hazards to be constant over the survival time I adopt the logistic specification, $h_{ik}(x) = 1/[1 + exp - (\beta' X_{ik-1}))]$ and estimate it by maximum likelihood, where h_{ik} represents a binary dependent variable and X_{ik-1} stands for lagged explanatory regressors that may vary over time. So, in practice this is equivalent to applying logit models in panel data, which becomes

[6]The model assumes that time-varying covariates are fixed within each period of time but can change across them.

easy to estimate once each individual's employment spells are split into discrete time units. I account for the fact that many observations represent the same individual by clustering error terms at the individual level.

The main concern in this estimation comes from the existence of individual time-invariant effects, μ_i, that help in explaining the binary choice of interest but cannot be observed. So, suppose that the actual model is formally:

$$Pr(h_{ik} = 1) = \Lambda(\gamma + \beta' X_{ik-1} + d_t + \mu_i + \varepsilon_{it})$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function, d_t refers to time effects and ε_{it} is the error term. If the individual specific effects are correlated with the rest of the included variables, then the estimates will be biased, because the individual fixed-effects will become part of the error term. Among the alternatives to solve this issue, the random-effects model of integrating out of unobservables also seems problematic in this setting. It relies on the assumption that the unobserved characteristics are orthogonal to the included regressors, which appears unrealistic given the evidence on the sorting of individuals into occupations based on their abilities and preferences. Conversely, the fixed-effect model has been argued to be problematic for nonlinear models (except in the poisson model) because of the incidental parameters problem (Neyman and Scott, 1948). This does not arise in the linear specification because the fixed-effects are easily dropped out by differencing or by estimating in deviations from means. Given that this is not possible in nonlinear cases, the parameters to be estimated in the model, μ_i along with the coefficients of the vector β, increase with sample size ($N \to \infty$). Thus, if each μ_i is treated as a parameter to be estimated using the available information on the individual, T_i, the maximum likelihood estimator is generally inconsistent and biased because T_i is fixed and usually small. The literature is still unclear, however, on the magnitude of these biases but suggests that panels of at least 8 units length per each subject in the dataset (T_i) produce unbiased estimates (Greene, 2011). My approach here is to use the fixed-effects specification, but in order to avoid the previously mentioned potential bias I restrict the sample being analysed by the fixed-effects specification to only those individuals that are observed at least

8 times in the dataset, similar to the approach followed by Topel and Ward (1992)[7]. Note that since the model is estimated based on within individual variation, rather than comparing movers to non-moving counterparts, just those who actually transition into self-employment (or any other state that implies switching the dependent variable from 0 to 1) contribute to the estimation and the rest are ignored. This implies that individuals were originally needed to be observed over at least 3 periods, corresponding to a "success" and a "failure"[8] for each of them along with the required lagged information. Another advantage of the fixed- over the random-effects model is that the former is consistent, although not efficient, when $E(\mu_i|x_i) = 0$, but the reverse does not hold.

The single discrete-time model can be easily extended to include different destination outcomes, such as movements into paid-employment, self-employment as well as entries within the same or different industries. In this case the hazard rate takes the functional form:

$$h_{mk} = \frac{exp(\gamma + \beta'_m X_{ik-1})}{1 + \sum_{j=1}^{J} exp(\gamma + \beta'_j X_{ik-1})}$$

for each transition into state j and can be estimated by the standard multinomial logit techniques (Jenkins, 2005). This is easily implemented after the data re-organising already conducted for the single-exit model.

4.5 Data & Descriptive Statistics

4.5.1 Data

The data I use comes from the "Muestra Continua de Vidas Laborales" (MCVL) or the Longitudinal Sample of Working Lives, which is a 4% non-stratified random drawn from the Spanish Social Security records. This includes individuals that are working or receiving unemployment benefits or pension at any time during the reference year. New individuals that are workers or pensioners for the first time are introduced in the sample every year to replace those who cease to have any relationship with the

[7]Specifically, Topel and Ward (1992) restrict the analysis to individuals observed over at least 13 years.

[8]That is, not moving in one period and moving in another one.

Social Security and as a mechanism of maintaining the 4% representative level given the ongoing increase of the reference population.

Note that although the MCVL includes information on active (workers and unemployment benefit recipients) and non-active (those in receipt of a pension and individuals paying national insurance without being employed) populations these do not represent the total active and inactive labour populations. It excludes some of the civil servants paying into a different social assistance system (i.e., "Clases Pasivas y Mutualidades") and unemployed people that do not get any benefit from the Social Security in the first place, and it also ignores many other non-active groups such as students or individuals taking parental leave of absence. However, the Social Security System covers 95% of the employment relationships in Spain (Durán, 2007).

The longitudinal character of the database allows the employment relations of individuals to be tracked from the first year they are included onwards, but it also contains retrospective information about their previous relationships with the Social Security that can be used to reconstruct their entire employment history. Studying labour market conditions prior to the initial year 2005 can be nevertheless problematic, since the sample will no longer represent the reference population at the given year, especially the further we look back in time (Felgueroso *et al.*, 2010). In this study I use MCVL waves from 2005 to 2010. Details of the matching and construction of the dataset are described in the appendix B.

From this initial dataset I select individuals that have been in employment at any time from 2005 to 2010. In particular, I focus on paid-employed workers contributing to the general regime of the Social Security System. In other words, removing those who pay their contributions through a special agreement and, therefore, do not represent an employment relation consistent with others observed in the database. I restrict the analysis to individuals not living in Ceuta or Melilla[9] and those who are aged between 18 and 65 years.

Given that earlier studies vary in their measures of entrepreneurial entry, it seems necessary to be clear that what I am examining here are flows into self-employment.

[9] I exclude autonomous cities of Ceuta and Melilla, two enclaves in North Africa, because their limited comparability with the rest of Spanish regions.

Specifically, I take the definition in the Spanish Security System that establishes the criteria on who is required to contribute to the special regime as a self-employed person. So, the self-employed represent workers above the age of 18 who run a lucrative economic activity on their own and without being tied to any labour contract as an employee. However, it also includes managing directors of limited companies ("sociedades mercantiles capitalistas") that conduct their activities on a regular basis and own the direct or indirect control of the business. Hence, it constitutes an heterogeneous group of individuals working on their account (Hurst and Pugsley, 2011; Parker, 2007): from skilled craftsmen and professionals that employ no or a low number of employees, to individuals creating more complex (and usually bigger) organisations. This reveals that the motivations, growth ambitions and strategic focus, for instance, could substantially differ within the group, and many of them, as many authors criticise, may not match with the traditional traits that entrepreneurship theories claim to characterise entrepreneurs. In contrast, self-employment as a measure of the incidence of entrepreneurship is appealing and widely used in this context (Elfenbein *et al.*, 2010; Parker, 2009b; Sorensen, 2007; Nanda and Sorensen, 2010; Hyytinen and Maliranta, 2008) because it is easy and objective to apply, especially when the focus of analysis is at the individual level and regarding the employment status, like in the present one.

I use the common approach of excluding individuals working in the agriculture sector from the analysis (Hurst and Lusardi, 2004; Sorensen, 2007; Sorensen and Phillips, 2011; Parker and Robson, 2004; Meager, 1992; Blanchflower, 2004), since self-employment rates are particularly high in this sector and cannot be readily compared to the rest of the industries. Moreover, higher self-employment entry rates from and into the agricultural sector over this period, and especially since around 2008, are highly attributed to changes in regulations. Since 2008 individuals working in the agriculture sector and owning the working farm have been introduced into the Social Security regime for self-employed from their previous special regime for farmers (by the Law 18/2007). Finally, I restrict the sample to the employment in the private sector.

In total, this leaves an initial sample of 841,194 individuals that are observed on average 15.9 times (i.e., quarters) over the whole period (i.e. 13,387,321 observations in total). Naturally, this sample gets reduced when introducing covariates in the regression analysis that contain missing values.

4.5.2 Descriptive Statistics

I begin by looking at how the self-employment entry rate evolves over the period 2005-2010. Figure 4.3 presents the number of employees that becomes self-employed as a fraction of the employment in the private sector the quarter before the entry. As the graph shows entry into self-employment peaks in 2007, noticeably declines since the start of the recession in mid-2007s and remains stable from 2009 onwards. Compared to the trend in unemployment shown in figure 4.2, this decline appears to correspond to the time that the unemployment rate starts to rise steeply. Similarly, the later fairly steady self-employment entry rate occurs whilst there is a slowing down in the rise in unemployment. As expected, the pattern of the self-employment rate shown in figure 4.4 looks very different and confirms the importance of making the necessary distinction between flow and stock analyses. The self-employment rate actually increases as the labour market conditions worsen over the recession, which is driven by a deeper decline in the stock of employees relative to the decrease in the number of self-employed in the labour market. Further insights about the exit rates from self-employment compared to paid-employment however, although interesting, lie outside the scope of this study.

A closer look at self-employment entry rates by the size of their former employer (figure 4.3) confirms that most self-employed people transition from small firms. The fraction of the self-employed coming from the smallest firm size categories, however, decreases more sharply than the rest, yet they still constitute the main source of self-employed individuals. While this already seems to suggest that increasing unemployment leads to lower self-employment entry flows, especially affecting moves into self-employment from smaller firms, more careful conclusions are drawn in the following sections.

Table 4.1 provides summary statistics for individuals in paid-employment in the first quarter in 2005, 2007 and 2010. Differences between the periods before and during the crises are apparent, caused, presumably, by the downsizing and closing of firms during the latter period. A larger share of permanent workers together with longer average tenure and labour market experiences indicate that dismissals are concentrated among youngest workers with temporary contracts. While the distribution of employment across firm size categories shifts towards both extremes, that is, to the smallest and largest size categories, suggesting that middle-sized businesses have migrated into the smaller firm categories over time, I cannot assess the importance of new firm entries and exits in these changes. As expected, the ratio of dismissals to voluntary resignations increases as the recession worsens.

4.6 Regression Results

4.6.1 Explaining Employee Mobility

I now analyse the relationship between employee turnover and the size of the employer and unemployment levels. Table 4.2 reports fixed-effects logistic hazard models for the probability of the worker moving to a new employer or into self-employment. The base category (zero) represents staying in the same firm. I control for a wide range of variables including job market experience, firm tenure, occupational level (skilled, semi-skilled or unskilled)[10], full-time job, permanent contract, industry, quarter and year-industry effects in all regressions. Firm tenure is the sum of the days that each worker has been working for the same employer, including all contracts that may have previously existed. Likewise, job market experience sums all working days that each individual has contributed to the Social Security system.

The baseline model in column 1 shows that the probability of job change declines monotonically with firm size. The negative coefficient of unemployment reflects that the hazard of turnover moves procyclically, meaning that the probability of employee

[10]Skill levels are determined by the qualification requirements of the occupation defined by the Social Security contribution groups. Following García and Muñoz (2011) I classify the existing 10 contribution groups into: 1) skilled workers: engineers, graduates and chief and departmental heads; 2) semi-skilled workers: clerks, auxiliary workers and skilled labourers; and 3) unskilled workers: semi-skilled and unskilled labourers. These do not necessarily match with the educational attainment of individuals, since workers are many times overqualified for the job they perform. Indeed, this seems to be a common case in Spain, where the highest incidence of overeducated workers among OECD countries is found (Verhaest and Van der Velden, 2010).

mobility declines with adverse labour market conditions. This might be a result of lower levels of hires in the economy overall and, therefore, more limited opportunities in the labour market. This would on one hand reduce the motivation of workers to resign and additionally, fewer workers would be able to find a job after being dismissed, although more separations would be expected to occur (Bruyere *et al.*, 2011). Column 2 introduces interaction terms between unemployment and firm size categories and confirms the negative direct relation between firm size and employee mobility. Likewise, the effect of unemployment remains negative and bigger in magnitude, yet the positive coefficients of the interaction terms indicate that the negative effect of unemployment is attenuated and even reversed the smaller the size of the firm. Or to put it another way, the higher probability of turnover from the smallest firms, namely microfirms (i.e., with less than 10 employees), more than offsets the negative relationship between unemployment and job change. The overall effect of unemployment on the turnover hazard, however, remains negative for larger firms (i.e. with more than 10 employees).

The rest of the included variables affect employee mobility in the expected directions, except firm tenure. Despite the well documented evidence of higher probabilities of employee turnover at low tenure levels (Topel and Ward, 1992; Farber, 1999b) I find a positive effect of current firm tenure on employee mobility. I speculate that the expected negative effect is probably captured by the highly positive effect of permanent jobs on turnover. As mentioned earlier, the Spanish dual labour market exacerbates the destruction of temporary jobs and leads to a greater rotation of workers with fixed-term contracts, which are by law shorter than 2 years[11] (García-Serrano, 1998). This argument would also explain the higher turnover of unskilled employees, as it has been documented before (Güell and Petrongolo, 2007; García and Muñoz, 2011), exhibit high rotation from temporary contracts to new contracts of the same kind.

What is missing from this analysis is the fact that employment relations can terminate by a voluntary decision of the worker (resignation) or a decision taken unilaterally by the employer (dismissal). As already argued, an important component of the empirical identification is that the MCVL provides information about the reason for the

[11]By the reform in 2006 (Decree 5/2006) the maximum duration of temporary contracts for each worker in a firm was reduced from 3 years to 2 years. Workers could be hired for shorter periods, but the sum of them could not exceed the 2 two years restriction within a period of 30 months.

individual leaving their current employer, which I expect to vary as the economy slows and may operate differently in firms of different size. Thus, in the next model (column 3) I examine the probability to be dismissed, compared to the probability of staying in the same firm or leaving the firm voluntarily. This information is taken from the Social Security records as the contract termination reason provided by the employer as part of a compulsory administrative procedure. Employees in the smallest firm size category (i.e., microfirms, with less than 10 employees) are found to be more likely to be dismissed, although in this case the effect of firm size is not monotonically decreasing. Workers in larger firms (i.e., with more than 10 employees) exhibit a lower probability to be dismissed than workers in largest firms (i.e., with more than 250 employees). As expected, having a temporary contract explains a substantial proportion of the probability of an individual to be dismissed.

Another possible approach that I have examined to assess the impact of dismissals in the turnover probability is to include dismissals as an independent dummy variable in a model similar to the ones shown in columns 1 and 2. I present the results in table B.1 in the Appendix B. As expected, dismissals turn out to be the main factor explaining the probability to change the employer. Although this finding is interesting in that it demonstrates that turnover decisions are mostly involuntary it must be taken with caution, hence the reason to leave it for the appendix. My concern about including it in the main text arises because dismissals in the vast majority of cases, unless the job is seasonal and the individual is again hired by the same employer with no other job spell between them, necessarily imply changes in the employer. This means that introducing dismissals on the right- hand-side can constitute almost a "tautology" and make causal relationships difficult to infer.

4.6.2 Explaining Transitions into Self-Employment

As the results in the previous section suggest omitting the cause of the individual leaving their current employer means ignoring the fact that the motivations to move across firms, and presumably across occupations, vary by firm size. So, a key question is whether the general cause of the individual leaving their current employer (namely voluntary resignations or dismissals) exerts any influence in the moves into self-employment and affects the firm size effect during the recession.

First, I re-estimate the equivalent models to the ones above but considering entry into self-employment as the dependent variable. Table 4.3 (columns 1 and 2) shows that the story for transitions from paid-employment to self-employment is fairly identical to the turnover analysis. The baseline model in the first column shows that the coefficients on firm size are positive, monotonically decreasing and slightly larger in magnitude than before. The effect of unemployment appears to be bigger and still negative. Column 2 contains the interactions between unemployment and firm size as before. Despite the larger direct negative effect of unemployment, the interaction terms are also larger than in the turnover model and confirm that the negative effect of unemployment is larger for larger firms. Overall, the small firm size effect persists. The probability of moving to self-employment increases by 1.3 percentage points for employees coming from the smallest firms (with less than 10 employees), by 0.6 for those coming from firms between 10 and 19 employees, by 0.3 for firms between 20 and 49 employees and by 0.1 for firms between 50 and 249 employees. Figure 4.5 summarises how the firm size effect varies along the distribution of unemployment, which indicates that the small firm size effect is intensified during adverse economic times.

In column 3 I introduce dismissals as an independent variable in the model to explain the probability to become self-employed. As expected from earlier results, dismissals exert an important positive and significant effect in the move into self-employment. When introducing interactions between firm size and dismissals (column 4) the estimates indicate that the effect of small firm size increases with prior dismissal from the job, especially for those coming from small firms with less than 20 employees.

Table 4.4 presents an alternative method to analyse the transition into self-employment as a means of isolating the turnover decision from the decision to become an entrepreneur. One concern which relates to the previous regressions is that the move into self-employment might be strongly associated with the higher level of employees leaving small firms, as the results actually suggest, and therefore say little about firms in shaping entrepreneurial skills and values as the theory suggests. To further investigate this, I estimate logit regressions for the probability of self-employment entry conditional on mobility (that is, restricting the sample to only employees changing their employer or becoming self-employed) as opposed to starting a new job in another firm. I use clustered standard errors to account for the repeated observations for each individual, since the fixed-effects specification is no longer feasible in this setting.

Once again, the same patterns of former employer's firm size and unemployment are observed (column 1). This reinforces the earlier results on the higher probability of self-employment among workers coming from small firms and the procyclical relationship between unemployment and self-employment entry. Nevertheless, most of the interaction terms between unemployment and firm size become insignificant, except for the businesses above 50 employees which when compared to the largest size category (over 249 employees) show lower rates of self-employment entry as unemployment rises.

Not surprisingly, the effect of having been dismissed turns out to be significant but negative now. This suggests that dismissals are the main drivers of turnover decisions but have a negative influence on the decision to engage in self-employment. When interacting with firm size (column 2), however, the same pattern as the one I observed before emerges; workers that have been dismissed from small firms are more likely to move into self-employment. One explanation could be that workers from small firms find more limited wage work opportunities after being dismissed. But it could also be the case that a higher proportion of individuals losing their jobs from small firms find themselves able to work as self-employed and find that losing their job provides them with the stimulus to try it, as opposed to workers in large firms that may not even consider this as an alternative way of generating revenue.

Once controlling for employee turnover, one can also see that workers leaving an occupation that requires high qualifications are more likely to become self-employed. Conversely, workers performing jobs with lower skill are associated with moves to new paid-employment contracts. Firm tenure is again positive and significant, which may suggest that longer working spells within a firm are positively associated with greater learning outcomes and consequently, with higher probabilities to start working on one's account.

4.6.3 Reemployment Transitions from Unemployment

Another approach is to study transitions into self-employment in the sample of dismissed workers. This way the opportunity cost argument becomes irrelevant to explain the greater turnover of workers in small firms[12]. If any small firm size effect is left, this should be driven by the development of entrepreneurial skills while in employment or by persisting sorting effects[13]. The main limitation of this approach is that the dataset only contains information about individuals having any relationship with the Social Security, therefore I cannot make any inference about unemployed people non-eligible for unemployment benefits and those with expired benefits, as I cannot check what happens to them or indeed whether they remain in the labour force. I, therefore, look at unemployed people receiving the unemployment benefit, and specifically those getting the unemployment insurance[14][15].

In Spain the unemployment insurance is paid to workers that have been dismissed from a job and have been contributing to the Social Security for at least a year within

[12] Despite I have already controlled for the last salary with the same aim in the previous section, this is not sufficient to control for differences, for example, in better promotion opportunities, hence higher expected future salaries, in large firms that may hinder employees leaving voluntarily their job.

[13] In the previous models I have already tracked workers the following quarter after the dismissal takes place (tables 4.3 and 4.4). This assumes that workers find a job or start their own business quickly after being dismissed and do not request any unemployment benefit or they earn it for too short period to be observed as unemployed in the quarterly dataset. Yet in practice, many workers remain unemployed for a longer period, especially the higher and longer the unemployment benefit they are eligible to receive as these will disincentive accepting any available job (Jenkins and García-Serrano, 2004; Bover *et al.*, 2002; Katz and Meyer, 1990).

[14] Although I could also track unemployment assistance recipients these can be qualified to get it for reasons that have nothing to do with the termination of an employment relation and lie outside the scope of the study.

[15] I would ideally look at workers displaced by economic, organisational, technological or productive causes or by collective dismissals in order to ensure that dismissals are not a consequence of unsatisfactory working performance and therefore, a non-random sample of employees with lowest productivity levels. The MCVL contains information on the specific cause of the dismissal, including the mentioned ones, but these represent a very low proportion of the total. The labour market reform in 2001-2002 allowed employers to terminate contracts by assuming that the dismissal was unfair and depositing the highest severance payment of 45 days' wages per year worked in court, as a means of avoiding costly procedures to get the administrative approval for objective dismissals. This practice, known as "express dismissal", has a widespread use and constitutes the vast majority of dismissals under the category of involuntary dismissals in the Social Security records. This is confirmed by the increase in the number of involuntary dismissals since the start of the crises, while the collective dismissals and those justified by economic objective causes have remained stable. For example, while collective dismissals have represented 0.1% of the total separations in both 2005 and 2010, involuntary dismissals have raised from 68% to 73% over the same period. As expected, voluntary leaves have decreased from 26% to 16%. Hence, I use the pool of involuntarily dismissed workers merged with the two categories of collective dismissals and displacements based on economic reasons, to study the move from unemployment into self-employment, as I expect the proportion of layoffs for disciplinary behaviour or poor performance to be relatively small in the analysed period.

the last 6 years before the dismissal. The length of the benefit is determined by the period that workers have being contributing to the system, ranging from the shortest 120 days of duration up to the maximum of 720 days. It pays 70% of the "regulatory base" or gross salary for the first 3 months and 60% thereafter, as far as the amount is above the statutory minimum wage and below a ceiling that is conditioned by the number of dependent children under 26. I have no direct information about the length of the unemployment insurance entitlement but I can control for the elapsed duration and tenure in the last job as an approximation.

There are two possible outcomes after a period of unemployment that I am considering here; returning to paid-employment or working as self-employed. An interesting question is to see if the recession has altered the probabilities of either of these outcomes and whether the determinants of exit differ by the outcome. This motivates the use of competing risk models, shown in table 4.5. When the unemployment insurance ceases because other reasons (which would actually represent other destinations, including the exhaustion of the benefit), these are treated as censored. The main concern that arises here is that I am not longer able to control for the unobserved individual heterogeneity that motivated the use of the fixed-effects estimator before. If I replicated the same specification as before I would restrict the analysis to individuals being unemployed for at least 8 quarters, because this ensures a "safe" use of the fixed-effects model, so I would end up missing valuable observations with shorter unemployment spells. That is why I prefer using the whole sample with clustered standards errors at the individual level to control for the correlation across observations on same individuals.

In addition to the set of control variables considered in the previous sections, I introduce two unemployment insurance related variables. First, I account for the time that the benefit has been paid, which starts counting closely after the termination of the contract, given the maximum of two weeks' notice to be eligible for the benefit. I define dummies for the intervals 1-5, 6-11, 12-17, 18-21 and 22-24 months to allow a flexible estimation of the elapsed time effect. This is motivated by the established empirical fact that the unemployment exit hazard rises around the exhaustion date of the unemployment benefit (Jenkins and García-Serrano, 2004; Card *et al.*, 2007).

I am, however, unable to compute any better measure that considers the time left until exhaustion, because data on the eligibility period is not available. This means that if someone who is entitled to a year of unemployment insurance postpones his or her return to work until the benefit is exhausted, this would be reflected on the third duration dummy and not on the latest. So a careful interpretation of this variable is needed, which captures not only changes in the probability of reemployment based on the time to exhaustion, but also the length of the benefit that each individual is eligible for. Since the latter depends on the time that the worker has contributed to the system, including tenure with the previous employer, will help to isolate the effect of interest. Second, I include the (log of) unemployment insurance payments per day that each person receives.

Table 4.5 (column 1) shows that the small firm size effect persists even in the move from unemployment to self-employment. The effect of the last employer's size is strictly monotonically decreasing, as before, although the effect is smaller for the lowest categories now. Interestingly, the effect is positive for the paid re-employment hazard. Both moves are negatively affected by the economic downturn, and particularly for the decision to become self-employed.

If the unemployment insurance plays any disincentive role in the re-employment decision this will be picked up by the firm tenure and unemployment benefit or salary variables, which reflect the length of time benefits are paid and their level. As expected, the former has a negative effect on any of the unemployment exit hazards and confirms that the longer the period for the eligibility of the unemployment insurance the less likely it is to exit unemployment. Note also the sharp rise in the self-employment and paid re-employment hazards at 22-24 months, the official maximum length of the benefit, for both exit destinations. By contrast, the level of the benefit payments increases significantly the probability of re-employment, and in particular, the likelihood of setting up as self-employed: a percentage change in the unemployment insurance payments is associated with an increase of 0.96 percentage points in the probability of becoming self-employed. Likewise, the effect of the wage in the previous job has a positive, though slightly lower effect. This would somehow contradict the consensus that unemployment benefit levels disincentive re-employment hazards, although these are usually referred to in the context of the move to paid-employment rather than into self-employment. Moreover, even the former have been found to exert small effects in Spain (Jenkins and García-Serrano, 2004). This could be interpreted as a less important disincentive response to the benefits among prospective entrepreneurs, which might be actually offset by a positive effect of liquidity on entry. In fact, this is consistent with the finding that individuals being dismissed from a permanent job, and therefore received a more generous severance payment, are significantly more likely to become an entrepreneur.

As previously stated, the firm size results could still be due to the sorting of individuals based on certain preferences and abilities in small firms in the first place rather than to any entrepreneurial learning mechanism while in employment. As an indirect way to disentangle these potentially overlapping effects, I decompose self-employment entries into moves made within the same industries, measured at the 3 digit level, and different industries. The underlying logic is that if any treatment effect takes place in the workplace previous firm size will exert greater effect when analysing entry in the same industry, because entrepreneurs will be able to bring greater knowledge and experience to the new business and benefit more from their social connections (Sorensen and Fassiotto, 2011). If no difference across both entry types is found, one could conclude that the size effect is the result of pure sorting. The results in table 4.6 support the existence of treatment effects: the greater probability of becoming self-employed after being dismissed from a small firm is accentuated for entries in the same industry.

4.7 Conclusions

Most entrepreneurs set up their business after having worked in a small firm. In this chapter, I show that this is particularly true during adverse economic conditions. During recessions businesses reduce their hires, leading to a lower number of job opportunities in the market and less workers resigning to improve their job satisfaction or status. Conversely, while more jobs are destroyed due to the closing and downsizing of firms, those who find themselves out of a job are left with scarcer employment alternatives. These lead to changes in the incentives to change jobs and become self-employed. I examine these moves among the career histories of a large sample of Spanish workers from 2005 to 2010. This setting is attractive owing to the dramatic rise in unemployment from mid 2007 onwards in Spain, following favourable conditions until then.

The picture drawn from the self-employment entry analysis is fairly identical to that of the turnover. However, dismissals are identified as the most important determinant in the decision to move into self-employment, which suggests that many would not have started working on their own account unless they had been dismissed. Although this is consistent with the view that economic adversity increases the rates of entrepreneurial entry, I find that higher rates of unemployment are associated with lower turnover and self-employment entry probabilities. The relationship between unemployment and self-employment entry propensity, however, appears to be influenced by the size of the former employer. The smaller the firm the worker has worked in, the more attenuated the negative effect of unemployment becomes. This could be partly explained by the higher probability of being dismissed among workers in small firms. Taken together, this has been reflected in an overall larger flow of employees from small firms moving into self-employment during the latest recession in Spain.

The results also indicate that the effect of previous employer's size is robust when considering self-employment entry among unemployment insurance recipients. The magnitude of this effect becomes much larger when I analyse entry within the same industry that the unemployed person last worked in. I interpret this finding as evidence of the shaping of abilities and attitudes towards entrepreneurship in the small firm workplace. If simple preferences and innate abilities were driving the self-selection of individuals across firm sizes and entrepreneurship, no difference would have emerged in the industry decomposition. Likewise, the fact the firm size estimates remain significant in the initial regressions after controlling for the unobserved individual heterogeneity, also suggests that workplace characteristics play an important role in the entrepreneurial entry decision process.

This finding is consistent with other non-industry specific works analysing the move from wage-work to self-employment and showing a negative effect of firm size on the propensity of entrepreneurial entry. As previously mentioned, this contradicts industry specific studies where larger (and better performing) firms are found to spawn more spinoffs. This inconsistency could arise not only because industry studies have mainly focused on infant and growing industries whereas studies on general labour market transitions pool all industries at different stages of development and age in the sample (Klepper, 2009), but also because the measure of entrepreneurship differs across them. The former have most often considered new firm founders, or spinoff companies themselves, as the unit of analysis (Agarwal *et al.*, 2004; Hvide, 2009; Gompers *et al.*, 2005). This has been indeed the result of the procedures followed to identify intra-industry spinoffs, by identifying newly established incorporated firm founders in a given industry and tracking their employment histories back to define their last employer as the "parent" firm. In contrast, studies using employer-employee datasets, such as this one, have usually relied on conceptually broader measures of entrepreneurship, most typically that of self-employment. Hence, an important question that remains to be answered is the extent to which the contradictory findings on the firm size effect are due to definitional differences. It seems possible that a substantial proportion of workers moving from jobs in small firms to self-employment do not get involved in the setting up of an incorporated firm, but start working as a skilled craftsman or professional or alternatively, creating a non-incorporated firm, which get excluded from the target population of industry specific studies.

The results have also direct policy implications. Although I am unable to verify the earlier conjecture on whether the overrepresentation of self-employed coming from small firms during economic downturns implies an increase of flows into activities with lower growth and employment potential, the results do reveal that most self-employed entries are motivated by a dismissal and within the same industry. So if self-employment is used by a considerable number of entrants as a response to scarce paid-employment opportunities and as a means to escape from unemployment we could expect them to perform worse in the short to medium term. Previous studies, in fact, indicate that self-employed or new firm founders that start their activities following dismissals have higher failure rates (Carrasco, 1999; Evans and Leighton, 1990; Eriksson and Moritz Kuhn, 2006). Moreover, given that the lack of employment options seems to be a more important motivation factor rather than pursuing a business opportunity, most of these businesses might replicate or imitate what their former employer was already doing instead of developing on new products or processes. Despite replicative entrepreneurship contributes to society by being the source of income to families that in many cases would otherwise have difficulties in being financially independent, in the sense that these businesses act as a wage substitute, innovative entrepreneurship is understood to serve as the basis for economic growth (Acs, 2008). Innovative entrepreneurship can be also a more effective way to reduce unemployment, since these businesses are more likely to grow as they, on average, generate more jobs. In fact, the vast majority of small businesses do not grow nor expect to do so in the future (Hurst and Pugsley, 2011), so having a high self-employment entry rate may not be sufficient to ensure sustainable job creation. Thus, a reflection about the kind of entrepreneurial activity that is expected to provide greater social returns should be at the basis of any public programme aiming to foster self-employment and micro-enterprises, especially in the light of the current government budget constraints and worsening economic climate. This calls for further research to assess differences in the performance and survival of the self-employed with respect to the reasons that led them to leave their last job, namely distinguishing between voluntary resignations and dismissals, and the size of their last employer.

Figure 4.1: Unemployment rate across Spanish provinces, 4th quarter in 2010

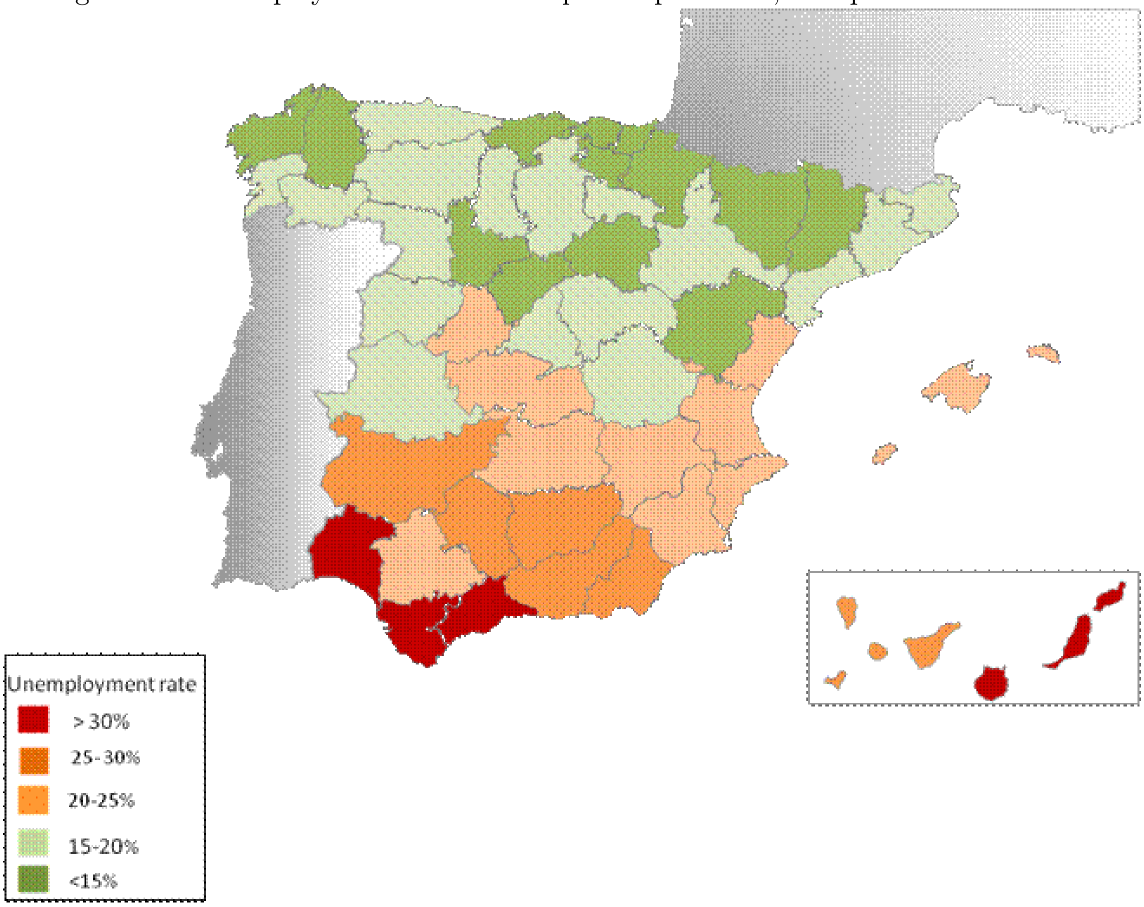


Figure 4.2: Unemployment rate in Spain, 2005-2011

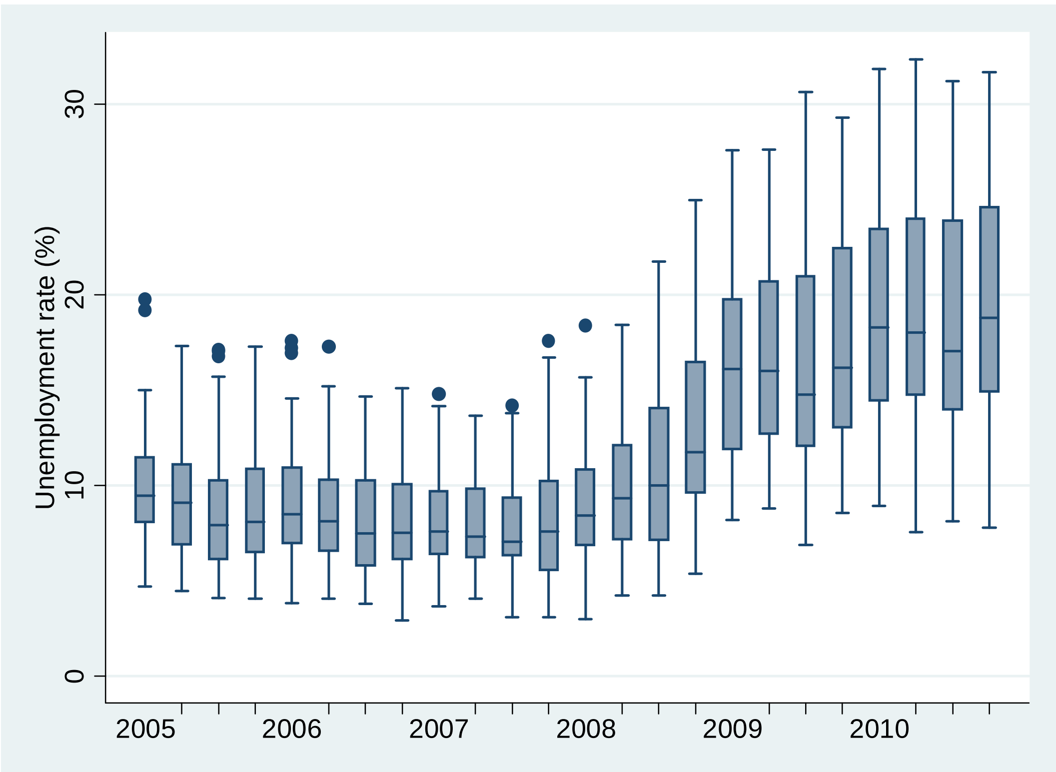


Figure 4.3: Self-employment entry rate. Overall and by last employer's firm size

Figure 4.4: Self-employment rate in Spain, 2005-2011

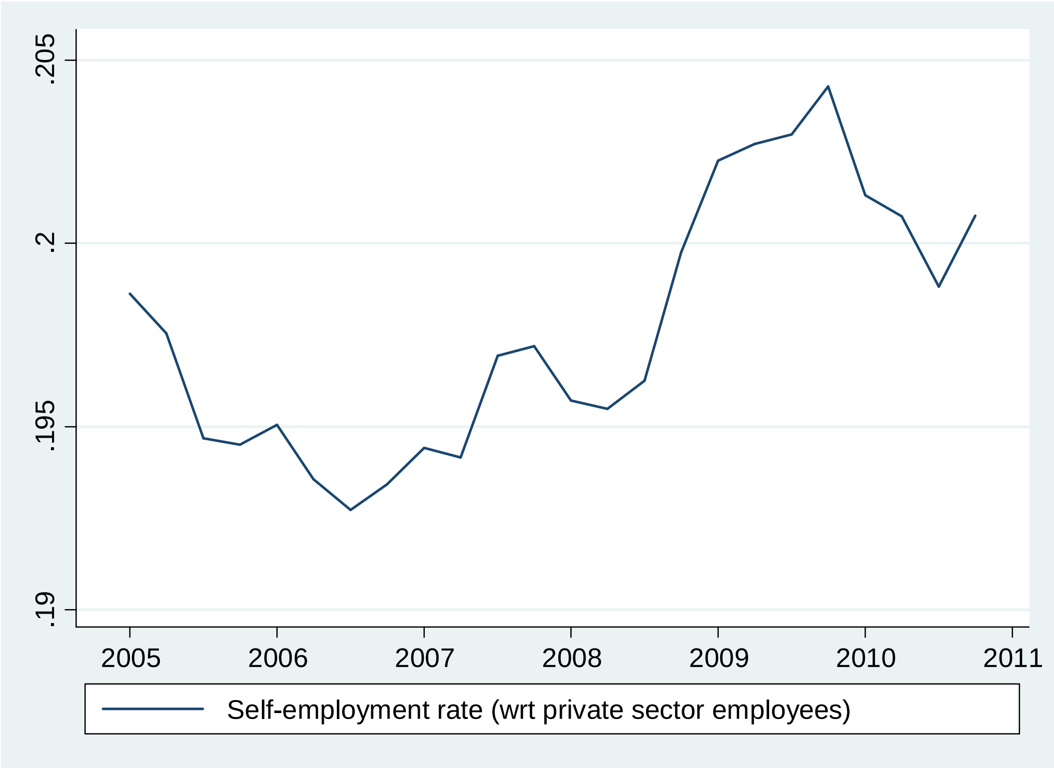


Figure 4.5: Marginal effects of firm size over unemployment levels

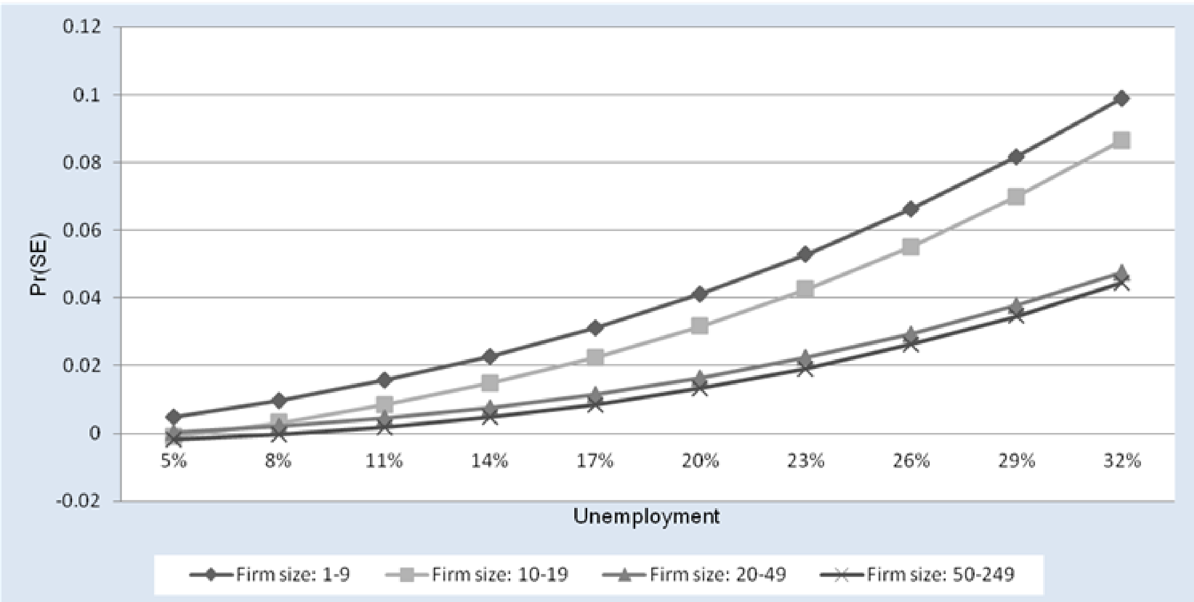


Table 4.1: Summary statistics. Distribution of workers across firm and employment characteristics

	2005Q1	2007Q1	2010Q1
Firm size: 1-9	25.8%	26.1%	26.6%
Firm size: 10-19	12.5%	12.5%	11.7%
Firm size: 20-49	17.5%	17.2%	15.8%
Firm size: 50-249	21.9%	22.2%	22.7%
Firm size: >249	22.3%	22.1%	23.3%
Paid-employment	80.1%	80.6%	79.9%
Self-employment	19.9%	19.4%	20.1%
Skilled	15.1%	15.9%	18.8%
Semi-skilled	56.2%	56.6%	56.7%
Unskilled	28.6%	27.6%	24.6%
Dismissals to resignations ratio	2.5	2.0	4.2
Permanent workers	70.0%	72.8%	78.0%
Full-time	85.8%	85.0%	80.3%
Female	39.3%	40.4%	44.2%
Tenure	5.0	5.0	5.9
Labour market experience	13.0	13.1	14.4
Age (employees)	37.4	37.8	39.3
Age (self-employed)	43.4	43.6	44.6

Note: All characteristics refer to individuals in paid-employment, unless otherwise specified.

Table 4.2: Determinants of the hazard of turnover and dismissals

	Prob (turnover)				Prob (dismissal)	
	(1)		(2)		(3)	
Firm size:1-9	0.659***	(0.01)	0.443***	(0.02)	0.231***	(0.01)
Firm size:10-19	0.361***	(0.01)	0.231***	(0.02)	-0.019*	(0.01)
Firm size:20-49	0.220***	(0.01)	0.137***	(0.02)	-0.112***	(0.01)
Firm size:50-249	0.069***	(0.01)	-0.000	(0.02)	-0.131***	(0.01)
Unemployment	-0.006***	(0.00)	-0.018***	(0.00)	0.013***	(0.00)
Firm age	-0.003***	(0.00)	-0.003***	(0.00)	0.002***	(0.00)
Job market experience	0.014*	(0.01)	0.014*	(0.01)	0.309***	(0.00)
Firm tenure	0.283***	(0.00)	0.283***	(0.00)	0.117***	(0.00)
Skilled	-0.559***	(0.02)	-0.558***	(0.02)	-0.267***	(0.01)
Unskilled	0.329***	(0.01)	0.328***	(0.01)	0.205***	(0.01)
Full time	-0.411***	(0.01)	-0.409***	(0.01)	0.155***	(0.01)
Permanent	-1.706***	(0.01)	-1.705***	(0.01)	-2.452***	(0.01)
Age	0.013	(0.01)	0.014	(0.01)	-0.004	(0.02)
Firm size:1-9 x unempl.			0.021***	(0.00)		
Firm size:10-19 x unempl.			0.013***	(0.00)		
Firm size:20-49 x unempl.			0.009***	(0.00)		
Firm size:50-249 x unempl.			0.007***	(0.00)		
Observations	2,748,055		2,748,055		4,453,029	
No. groups	187,228		187,228		293,345	
Pseudo R^2	0.099		0.099		0.120	

Note: Coefficients of logit regressions for turnover and dismissal probabilities; Standard errors in parentheses. All regressions also control for quarter, industry and year-industry fixed effects.
Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.3: Determinants of the hazard of transition into self-employment

	Prob (self-employment)							
	(1)		(2)		(3)		(4)	
Firm size:1-9	0.90***	(0.08)	-0.13	(0.14)	0.79***	(0.09)	-0.27+	(0.16)
Firm size:10-19	0.38***	(0.09)	-0.45**	(0.16)	0.45***	(0.10)	-0.56**	(0.18)
Firm size:20-49	0.19*	(0.09)	-0.12	(0.16)	0.28**	(0.09)	-0.15	(0.17)
Firm size:50-249	0.07	(0.08)	-0.27+	(0.15)	0.21*	(0.09)	-0.23	(0.17)
Unemployment	-0.02*	(0.01)	-0.09***	(0.01)	-0.02*	(0.01)	-0.07***	(0.01)
Firm age	-0.02***	(0.00)	-0.02***	(0.00)	-0.02***	(0.00)	-0.02***	(0.00)
Job market experience	0.20***	(0.04)	0.21***	(0.04)	0.01	(0.04)	0.01	(0.04)
Firm tenure	0.41***	(0.01)	0.40***	(0.01)	0.30***	(0.01)	0.30***	(0.01)
Skilled	-0.15+	(0.09)	-0.14	(0.09)	-0.18+	(0.09)	-0.17+	(0.09)
Unskilled	-0.03	(0.06)	-0.02	(0.06)	-0.14*	(0.06)	-0.13*	(0.06)
Full time	-0.27***	(0.06)	-0.26***	(0.06)	-0.31***	(0.07)	-0.30***	(0.07)
Permanent	-1.25***	(0.05)	-1.23***	(0.05)	-0.06	(0.05)	-0.07	(0.05)
Age	0.07	(0.05)	0.07	(0.05)	0.10	(0.07)	0.10	(0.07)
Firm size:1-9 x unempl.			0.09***	(0.01)			0.08***	(0.01)
Firm size:10-19 x unempl.			0.08***	(0.01)			0.07***	(0.01)
Firm size:20-49 x unempl.			0.03*	(0.01)			0.02+	(0.01)
Firm size:50-249 x unempl.			0.03**	(0.01)			0.03*	(0.01)
Dismissed					3.46***	(0.04)	3.05***	(0.11)
Firm size:1-9 x dismissed							0.49***	(0.12)
Firm size:10-19 x dismissed							0.67***	(0.14)
Firm size:20-49 x dismissed							0.36**	(0.13)
Firm size:50-249 x dismissed							0.25+	(0.13)
Observations	114,174		114,174		114,174		114,174	
No. groups	10,084		10,084		10,084		10,084	
Pseudo R^2	0.157		0.160		0.401		0.403	

Note: Coefficients; Standard errors in parentheses. All regressions also control for quarter, industry and year-industry fixed effects. Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4: Determinants of the hazard of transition into self-employment conditional on employee mobility

	Prob (self-employment|turnover)			
	(1)		(2)	
Firm size:1-9	1.325***	(0.08)	1.147***	(0.06)
Firm size:10-19	1.048***	(0.09)	0.766***	(0.06)
Firm size:20-49	0.901***	(0.09)	0.501***	(0.06)
Firm size:50-249	0.504***	(0.09)	0.314***	(0.06)
Firm size:1-9 x unempl.	0.002	(0.01)		
Firm size:10-19 x unempl.	-0.009	(0.01)		
Firm size:20-49 x unempl.	-0.023**	(0.01)		
Firm size:50-249 x unempl.	-0.015+	(0.01)		
Dismissed	-0.031	(0.02)	-0.283***	(0.07)
Firm age	-0.009***	(0.00)	-0.009***	(0.00)
Job market experience	0.003+	(0.00)	0.003+	(0.00)
Firm tenure	0.043***	(0.00)	0.043***	(0.00)
Skilled	0.424***	(0.03)	0.415***	(0.03)
Unskilled	-0.374***	(0.02)	-0.368***	(0.02)
Full time	-0.282***	(0.03)	-0.283***	(0.03)
Permanent	1.090***	(0.02)	1.089***	(0.02)
Age	-0.005***	(0.00)	-0.005***	(0.00)
Unemployment	-0.026***	(0.01)	-0.032***	(0.00)
Female	-0.503***	(0.02)	-0.501***	(0.02)
Immigrant	-0.027	(0.03)	-0.026	(0.03)
Firm size:1-9 x dismissed			0.330***	(0.07)
Firm size:10-19 x dismissed			0.297***	(0.08)
Firm size:20-49 x dismissed			0.244**	(0.08)
Firm size:50-249 x dismissed			0.039	(0.08)
Observations	536,551		536,551	
No. groups	267,810		267,810	
Pseudo R^2	0.091		0.091	

Note: Coefficients; Standard errors clustered at the individual level in parentheses. Sample only includes individuals that changed employer. All regressions also control for quarter and industry fixed effects.

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

Table 4.5: Competing risks hazard rate models for reemployment from unemployment to self-employment and paid-employment

	(1)		(2)		(3)	
	SE	Emp	SE	Emp	SE	Emp
Last employer size:1-9	0.646***	-0.439***	0.533***	-0.457***	0.664***	-0.407***
	(0.05)	(0.01)	(0.08)	(0.02)	(0.08)	(0.02)
Last employer size:10-19	0.446***	-0.275***	0.293**	-0.303***	0.359***	-0.251***
	(0.05)	(0.01)	(0.09)	(0.02)	(0.09)	(0.02)
Last employer size:20-49	0.357***	-0.204***	0.326***	-0.193***	0.346***	-0.155***
	(0.05)	(0.01)	(0.09)	(0.02)	(0.08)	(0.02)
Last employer size:50-249	0.196***	-0.079***	0.089	-0.043*	0.089	-0.028
	(0.05)	(0.01)	(0.09)	(0.02)	(0.08)	(0.02)
Unemployment	-0.030***	-0.003**	-0.016**	0.005***	-0.017**	0.006***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Last employer's age	-0.006***	0.002***	-0.006**	0.001*	-0.006**	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Job market exp.	0.009**	0.003***	0.011*	0.006***	0.003	0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm tenure	-0.019***	-0.059***	-0.036***	-0.046***	-0.027***	-0.051***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Skilled	0.642***	-0.157***	0.687***	-0.088***	0.491***	-0.288***
	(0.04)	(0.01)	(0.06)	(0.02)	(0.06)	(0.02)
Unskilled	-0.442***	0.098***	-0.570***	0.075***	-0.358***	0.141***
	(0.03)	(0.01)	(0.06)	(0.01)	(0.05)	(0.01)
Age	-0.037***	-0.012***	-0.042***	-0.012***	-0.037***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Permanent	0.306***	-0.297***	0.277***	-0.168***	0.262***	-0.227***
	(0.03)	(0.01)	(0.05)	(0.01)	(0.05)	(0.01)
Dur 6-11	-0.339***	-0.689***	-0.305***	-0.887***	-0.335***	-0.913***
	(0.03)	(0.01)	(0.06)	(0.02)	(0.05)	(0.01)
Dur 12-17	-0.558***	-1.050***	-0.424***	-1.237***	-0.610***	-1.377***
	(0.05)	(0.02)	(0.08)	(0.03)	(0.08)	(0.02)
Dur 18-21	-0.575***	-1.238***	-0.653***	-1.404***	-1.022***	-1.586***
	(0.11)	(0.04)	(0.19)	(0.06)	(0.18)	(0.05)
Dur 22-24	2.922***	2.322***	2.891***	1.874***	2.458***	1.744***
	(0.16)	(0.09)	(0.23)	(0.14)	(0.23)	(0.14)
Female	-0.698***	-0.017*	-0.669***	-0.043**	-0.531***	0.042**
	(0.03)	(0.01)	(0.05)	(0.01)	(0.05)	(0.01)
Immigrant	-0.009	-0.113***	0.028	-0.099***	-0.022	-0.114***
	(0.04)	(0.01)	(0.07)	(0.02)	(0.07)	(0.02)
Log last real salary			0.105***	-0.199***		
			(0.03)	(0.01)		
No. children			0.072	0.076***	0.091+	0.057***
			(0.06)	(0.02)	(0.05)	(0.01)
Log real UI benefits					1.069***	0.362***
					(0.07)	(0.01)
Observations	677,840		241,256		266,783	
No. groups	220,695		87,420		96,254	
Pseudo R^2	0.078		0.089		0.093	

Note: Coefficients; Standard errors clustered at the individual level in parentheses.

All regressions also control for quarter and industry fixed effects.

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

Table 4.6: Reemployment model from unemployment to self-employment: Same and different industry

	SE Diff. industry		SE Same industry	
	(1)		(2)	
Last employer size: 1-9	0.293***	(0.05)	2.037***	(0.15)
Last employer size: 10-19	0.213***	(0.06)	1.560***	(0.16)
Last employer size: 20-49	0.195***	(0.06)	1.261***	(0.16)
Last employer size: 50-249	0.093+	(0.06)	0.872***	(0.16)
Unemployment	-0.027***	(0.00)	-0.036***	(0.01)
Last employer's age	-0.002	(0.00)	-0.023***	(0.00)
Job market exp.	0.004	(0.00)	0.010*	(0.00)
Firm tenure	-0.026***	(0.00)	-0.001	(0.01)
Skilled	0.788***	(0.04)	0.435***	(0.07)
Unskilled	-0.431***	(0.03)	-0.547***	(0.05)
Age	-0.034***	(0.00)	-0.039***	(0.00)
Permanent	0.438***	(0.03)	0.066	(0.05)
Dur 6-11	-0.221***	(0.04)	-0.720***	(0.07)
Dur 12-17	-0.429***	(0.06)	-1.005***	(0.12)
Dur 18-21	-0.341**	(0.12)	-1.800***	(0.38)
Dur 22-24	3.139***	(0.16)	2.032***	(0.39)
Female	-0.633***	(0.03)	-0.599***	(0.05)
Immigrant	-0.015	(0.05)	-0.067	(0.07)
Observations	677,855		677,855	
No. groups	220,705		220,705	
Pseudo R^2	0.070		0.070	

Note: Coefficients; Standard errors in parentheses. Transitions to paid-employment omitted. Sig: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 5

Final Conclusions

5.1 Main Findings

The main goal of this work has been to reconcile the literature studying distinct traits and attitudes that make people more prone to entrepreneurship with the research stream that considers entrepreneurship as part of the general process of labour market mobility. In this thesis I have presented three main chapters assessing different dimensions of the transition of employees into entrepreneurship.

In Chapter 2 I have examined whether intrapreneurs, defined as those employed that get engaged in entrepreneurial activities for their employer, share the same traits as individual entrepreneurs. Given that they keep ties with their employer, i.e. they are still an employee with that employer, and hence do not actually take the risk of leaving their employment to become entrepreneurs, I expected them to share the same skills and attitudes as other employees. The empirical results have confirmed that unless intrapreneurs get further engaged in the new business by acquiring an ownership stake, they seem to have a different profile of attitudes compared to entrepreneurs which could explain why they are not engaging in independent venture set up. In particular, they lack entrepreneurial skills and observe less business opportunities available in the market.

Although this analysis has served as a starting point to confirm individual level differences across occupations based, in particular, in the distinction on whether individuals remain as employees like in the case of intrapreneurs or they cease their relationship with their employer, Chapter 3 and Chapter 4 have developed this by assessing how workplace characteristics can actually shape a workers' mindset and set of skills to make them more or less likely to move into entrepreneurship after they cease to be an employee (Sorensen and Fassiotto, 2011). So instead of taking entrepreneurial traits as given or exogenously determined, in these chapters I have considered that attitudes and, particularly, the skills are acquired as part of the employment history of individuals. Both chapters have drawn special attention to the size of the organisation employees have been working for, as its influence has been well established by the fact that many studies have shown that the majority of entrepreneurs are found to have set up their new venture after working for a small firm. The underlying rationale is that workers in small firms undertake a wider range of tasks, so that they acquire a set of balanced skills that are necessary when setting up a firm, and they also get exposure to a wider network of suppliers and customers many of whom are indeed small firms.

My work on the impact of human capital on spinoff formation in Chapter 3 has departed from earlier studies in that I have formalised how skills are acquired and transferred across jobs conditional on the size of the firm. That is, I have shown that the origin of whether an individual acquires balanced or narrow skills lies on the width of the set of tasks that employees perform, which in turn is a result of the size of the firm. Contrary to earlier views I have found that employees from both large and small firms are able to transfer the same overall value of task-specific human capital if they decide to become entrepreneurs, but the difference rests in that employees from small firms transfer more diverse knowledge. I have shown that the smaller the firm individuals are working for the wider the knowledge that workers will accumulate as a result of the limited division of labour. Therefore, given that the task-specific human capital is portable across firms or occupations whenever the latter requires performing the same set of tasks, workers from small firms will be able to transfer and apply their knowledge when moving into entrepreneurship. This occurs because the latter requires a wide range skills to perform the different roles involved in the setting up of a new venture (Lazear, 2004, 2005). This explains the finding (consistent with many other studies) why entrepreneurs coming from small firms are more likely to enter the same industry they were last working in. Conversely, I have shown that workers in large firms benefit from higher returns to their specific human capital, which translates into a higher opportunity cost of moving into entrepreneurship, as this would make part of their task-specific human capital unused. Only those employees with the best ideas will be willing to quit to develop the idea on their own and as a consequence, we will observe that the entrepreneurs coming from large firms will outperform those coming from small firms. I am aware that distinguishing between entrepreneurs that come from small firms and those that come from large firms is too limited to use as the basis to identify growth oriented businesses, nevertheless it opens the debate concerning the conception of small businesses as the best training grounds for prospective growth oriented entrepreneurs. So far, many studies have highlighted the central role of small firms in generating a large number of entrepreneurs (Wagner, 2004; Parker, 2009b; Sorensen, 2007; Elfenbein *et al.*, 2010; Hyytinen and Maliranta, 2008; Hvide, 2009; Gompers *et al.*, 2005) but they have hardly assessed how the businesses founded by entrepreneurs coming from small firms perform compared to those coming from large firms.

The point of departure in Chapter 4 has been to assess if the underlying assumption set out in Chapters 2 and 3 about the unilateral decision of employees to resign and move to entrepreneurship reflects the actual context in which individuals make career mobility choices. Previous studies have been silent on the cause of the termination of the contract, or have relied on the mentioned assumption that employees resign voluntarily the firm[1]. By analysing the career mobility patterns of a large sample of individuals in Spain, I have shown that dismissals are a key driver in explaining the transitions into entrepreneurship, especially when these affect workers in small firms. In principle, this finding does not contradict the view that small firms serve as incubators for potential entrepreneurs, as I still find support for the small size effect when controlling for the reason to terminate the employment contract (i.e., compulsory dismissals or voluntary resignations) and when looking specifically at a

[1]To be more precise, most of the studies explaining the existence of spinoffs focus on involuntary spinoffs, understood as the spinoffs that emerge after the interaction between the employee and the employer and results in employees leaving voluntarily the firm (Klepper, 2009). Thus, they pay no attention to spinoffs generated by individuals' own motivation to become an entrepreneur.

sample of dismissed workers. But still, it provides a new understanding about the dynamics that encourage individuals to move into entrepreneurship.

Assessing empirically whether workplace characteristics actually influence individuals' learning and mindset is not straightforward. While the question of interest, in this case, has been to examine the effect of firm size (treatment) on the probability of an employee entering entrepreneurship, one needs to bear in mind that the decision of individuals to work for a firm with certain characteristics can be largely affected by their preferences and skills, i.e. the assignment is not random, and hence the comparison of the outcomes of individuals from organisations with different characteristics becomes problematic. This means that the estimates of the treatment effect using simple regression techniques may be contaminated by selection bias. I have addressed this problem by using instrumental variables methods in Chapter 3 and running fixed-effects in panel data in Chapter 4. To the best of my knowledge, this is the first work using these techniques to disentangle the actual treatment effect from the effect of selection in this context. In both chapters, I have found support for the view that working in small firms does actually increase the subsequent likelihood to move into entrepreneurship. I have claimed moreover, that the treatment effect is associated with the acquisition of knowledge and skills, rather than just shaping workers' mindset and career motivations, since the magnitude of the firm size effect has turned out to be much larger in both studies when analysing entry into the same industry as the last firm the employee worked for.

Although my intention in this thesis has been to be descriptive, by providing evidence on the determinants of the entrepreneurial decision to set up a new venture, several results have direct implications for policy discussions on the support for entrepreneurship. First, the existence of a dual labour market, where insiders, holding a permanent contract, maintain strong security privileges and outsiders, workers with temporary contracts and unemployed (typically young workers), have low firing costs or no costs at all, seems to have an impact on the level and quality of the start-up activity. If, as I have argued, the workplace is a key training ground for prospective entrepreneurs, the dualism in the labour market will hinder outsiders' employment experience, hence the acquisition of skills, values and opportunities to encounter new business ideas. An excessive job turnover of temporary workers, who may get trapped into temporary work and are also the most severely affected by the economic downturn, moreover, may push individuals with less skills and knowledge about the industry into entrepreneurship, as the results in Chapter 4 have revealed. In particular, the findings have shown that dismissals are the most important determinant in the decision to transition into self-employment, which suggests that many would have not started working on their own account unless they were dismissed. And although contrary to earlier works I have found that those who have better positions within the firm are more likely to engage in self-employment, an excessive turnover among outsiders may hinder them from acquiring deeper industry knowledge and task-specific skills necessary to succeed as entrepreneurs. Conversely, in a context of dualism insiders' opportunity costs of leaving their place of employment to get involved in the setting up of a venture are higher. This study, therefore, contributes to the debate about the consequences and potential reforms of dual labour market institutions by providing a new awareness of its impact on new business creation beyond the usually claimed concerns about the increase in employment volatility or disincentives to provide on-the-job training to temporary workers. Although the impact on the entrepreneurial activity may not be as evident as an increase in layoffs or the hiring freeze during economic downturns, long term effects of the dualism on both entrepreneurship level and performance should not be neglected. This concern should be likewise relevant not only for the well known Spanish case, but also for the discussions on labour market reforms taking place in other European countries sharing dual labour market institutions, such as Italy, France or Sweden.

Moreover, the length of unemployment benefits seems to have a disincentive effect in the transition into entrepreneurship, as indicated in Chapter 4, similar to earlier results documented about general reemployment transitions. I have shown that the likelihood to exit unemployment, both to self-employment and paid employment destinations, increases sharply at 22-24 months, the official maximum length of the unemployment benefit. Schemes that allow an individual to receive the whole unemployment benefit in a lump sum if they decide to become self-employed, such as the one recently introduced by the Spanish government which targets youth and women unemployed, are likely to reduce the mentioned delay in the transition into entrepreneurship as well as to increment the start-up capital of those who create a business before their benefit expires.

However, there needs to be a careful consideration of the objective and scope of this kind of intervention, in an effort to design a coherent entrepreneurship policy. In particular, this should clearly define if the ultimate goal of the policy is to increase the overall number of the self-employed or rather the quality of the start-ups. This relates to the view that more entrepreneurship may not better, in the sense that a higher entrepreneurial entry rate per se does not necessarily lead to employment and economic growth (Blanchflower, 2004; Shane, 2009). In fact, public policies designed to increase the number of people that create new businesses tend to attract individuals with lowest opportunity costs, say unemployed or paid-employed with lowest salaries, who also tend to lack the necessary skills to create and manage a business and enter industries with low growth potential and high death rates (Anyadike-Danes *et al.*, 2005). I will come back to this point later in this section.

5.2 Limitations of the Research

Several limitations to this thesis have been already discussed in each of the corresponding chapters. Here, I will consider a number of gaps that have remained unanswered in my work and some limitations that affect the comparison of the findings across the chapters.

First, throughout my thesis I have studied entrepreneurial transitions from established firms. To do so, I have looked at the characteristics of the last employer, and ignored previous employment spells with other employers. This does not represent an issue in Chapter 3, because the framework in question encompasses the interaction of the employee with the current employer. This has been in fact the reason to consider only two periods in the theoretical model. That is, I have assumed that in the first period individuals work for a given employer where they accumulate task-specific skills, and at the end of the period they decide whether they switch to entrepreneurship or rather remain as employees in the firm. Nevertheless, when the focus has been on the skills and learning that can be acquired during the employment career a concern arises regarding past employment relationships. For instance, in Chapter 4 for the sake of simplicity and empirical feasibility I have only considered the characteristics of the last employer while in reality each individual in the dataset holds around 12 different labour relationships with a variety of employers. This work has been, therefore, unable to explain if previous job experiences in small firms have any influence in the transition into entrepreneurship, and more broadly, I believe that this may represent one of the main challenges of the current state of learning theories. Even empirically, one should ideally take into account if earlier work experiences in small firms also play a positive role in the transitions into entrepreneurship, for example, by including a variable accounting for the accumulated tenure in small firms during each individual's career history.

Furthermore, I should note that the present work implicitly assumes that the size of established firms remains on average stable over time. Otherwise, if the proportion of firms that were growing fast was high we would observe many employees working for large firms, while they were initially working in a small firm. Therefore, any interpretation about the firm size effect would be misleading.

Another theoretical gap concerns the reconciliation of some of the results in Chapter 3 and 4. One of the main findings that emerges from Chapter 4 is that the self-employed coming from small firms tend to do so after being dismissed. Moreover, both in Chapter 3 and Chapter 4 I find support for the view that small firms shape the abilities and attitudes of their employees which make them more likely to start-up a new firm afterwards. So taken together, if workers from small firms are better equipped to found businesses, one of the questions that remains to be answered is why they appear to wait to be dismissed to become entrepreneurs. The theoretical model presented in Chapter 3 offers the basis for a plausible explanation. Assuming that the rationale for individuals to move into entrepreneurship is based on the comparison between the expected returns they can obtain as entrepreneurs (both monetary and non-pecuniary) and the wage they can earn in paid work, dismissals can switch the final choice by altering the value of the latter. That is, as long as individuals keep their job their wage is understood to be higher than the expected returns they would perceive as self-employed, but if they are dismissed their wage in a new job might drop below the self-employment threshold. Hence, my finding on a larger positive effect of dismissals on the likelihood to move into self-employment for those being dismissed from small firms suggests that their post-layoff expected wage is lower than their initial wage. When this is combined with a greater decline in earnings for those in paid work then for workers leaving small firms during adverse economic conditions, we would observe, as revealed by the results in Chapter 4, a larger positive impact of dismissals on self-employment entry.

Finally, there is a note of caution when comparing the results from different chapters. While Chapters 2 and 3 explore the transitions to entrepreneurship using Global Entrepreneurship Monitor (GEM) data, hence relying on the definition used in the GEM framework and defining entrepreneurs as those individuals involved in the setting up of a business they own and manage, Chapter 4 examines entries into self-employment. In this last chapter I no longer use GEM data but the employment history of a large sample of Spanish workers included in the "Muestra Continua de Vidas Laborales" (MCVL) or the Longitudinal Sample of Working Lives MCVL provided by the Spanish Social Security. Self-employed according to the definition of the Spanish Social Security regulation encompasses individuals working for themselves irrespective of whether they hire employees and including managers who own the direct or indirect control of a business. Therefore, it includes individuals working on their own account but who do not actually found a new business, such as skilled craftsmen and professionals. And without entering in the discussion on whether self-employment fits with the theoretical notions that entrepreneurship entails, concerning risk taking or innovation for example, it is important to note that both measures in the present work are not equivalent. Especially because I am using self-employed and entrepreneur interchangeably when discussing common findings in this concluding section.

Ideally I would perform some robustness checks using different sub-categories of self-employed or even restrict the definition of the self-employed to those with employees, for example. However, the MCVL does not provide the required information to do so. Furthermore, I am also unable to measure the extent to which dependent self-employed are present in the sample, that is, self-employed that worked for a given firm as regular employees and became self-employed as part of the firm's strategy to increase flexibility and lower costs. Although it seems to be quite an extensive practice (Roman *et al.*, 2011) and we could expect it to have increased during the adverse economic climate, the dataset does not contain any information about the firms that the self-employed are working for.

5.3 Future Research

While so far most authors have been interested in exploring where entrepreneurs come from, this work has gone some way towards enhancing our understanding of how the origin (i.e., the employer context) can also impact the subsequent performance of new businesses. In particular, although my findings corroborate the fact that small firms spawn more entrepreneurs, the role of small firms has been put in perspective by pointing out that the quality of the entrepreneurs that emerge from them might be on average lower. As said, a key finding in Chapter 3 concerns the higher growth potential of businesses founded by former employees in large firms, driven as I have argued, by their higher opportunity costs of quitting the firm. The evidence in Chapter 4 has also suggested that dismissals have a greater impact in promoting self-employment entry among workers in small firms, who presumably choose entrepreneurship as a second-best response to adverse labour market conditions. Yet, I have not explored if any performance difference exists based on their reason to terminate their last employment contract and the size of the firm. The existing evidence in the literature suggests that those entrepreneurs that enter motivated by a dismissal perform worse, although we may expect a lower or no effect when dismissals occur massively and do not only affect workers with lowest productivity. Although the MCVL does not contain business level information to construct indicators to measure business performance, such as earnings, firm size or firm growth, studying the survival of the business for those entering self-employment seems a promising extension of the current work once new waves of data become available.

Further research is also needed to reconcile the findings between industry specific and non-industry specific works regarding the firm size effect. I conjecture that this inconsistency may be due to the use of different measures of entrepreneurship, as some of my results suggest. In Chapter 4, as in earlier studies examining transitions into entrepreneurship using self-employment data, the effect of firm size has turned out to be large, negative and highly significant. On the other hand, in Chapter 3, when analysing business founders as in most industry-specific works, the magnitude and significance level of the effect of size have been notably lower. This seems to suggest that many self-employed that come from small firms do not create a new business but carry out an economic activity on their own account, so they are excluded from industry specific works.

Future research could also concentrate on the investigation of several areas that have shown up in my research but I have not developed in more details because they were outside the scope of my thesis. For example, similar to most of the earlier studies exploring gender differences I have found that females are less likely to switch to independent entrepreneurship. The results in Chapter 4 have revealed that this is also true among unemployed individuals. Interestingly, however, in Chapter 2 I have not found any significant gender effect when analysing the probabilities to engage in intrapreneurial activities versus the rest of analysed occupational choices, namely independent entrepreneurship and the rest of employees. Although the coefficient indicated a positive propensity of males to involve in intrapreneurial activities, this was not statistically significant.

It would be also fruitful to conduct further work at the regional level using the MCVL, particularly in light of the divergence in unemployment across the Spanish regions that reflects underlying differences in their economic activity and performance. For example, over the years preceding the onset of the economic crisis, the construction sector, mainly concentrated around the Mediterranean coast, was driving the growth of the regions there and creating a large number of jobs. The employment in construction, however, has been the most severely affected over the last years. Furthermore, in some industries, such as in construction, agriculture or tourism, temporary contracts are more commonly used, because in many cases they are offered to conduct seasonal works. Further research could therefore investigate, if the present results in Chapter 4 are stable when including a series of variables controlling for the economic activity of the region and especially, variables referring to the state of the industry in the region where individuals are working in. Similar questions may also be raised regarding the location of the new business activities compared to the one of incumbent firms.

In sum, this PhD thesis has confirmed and reinforced the idea that the origin of entrepreneurs, by this meaning the previous employment experiences, is central in the understanding of entrepreneurial entry decision and subsequent performance of new businesses. I have mainly relied on occupational choice theories and human capital theories, whence the predominant view of entrepreneurship as a labour market status throughout my thesis. By doing so, I have contributed, in broad terms, to the convergence between the literatures on entrepreneurship and labour economics. This has also been reflected in the statistical methods I have used and empirical issues I have been concerned about. For example, I have been careful about the empirical strategy when inferring any causal interpretation, as modern applied labour economics and more broadly miroeconometrics suggest, yet most research on entrepreneurship has not fully adopted. Likewise I have exploited the advantages of panel data whenever possible and I have used instrumental variable techniques when analysing cross sectional data, in both cases as means to solve self-selection issues.

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Appendix A

Appendix Chapter 3

A.1 Description of Data Collection

The collection of data for this study has been conducted through an extension of the 2010 Global Entrepreneurship Monitor (GEM) adult population questionnaire in the UK, Based on the existing standardised set of questions in GEM I have introduced follow-up questions on each individual's current or recent employment status that have allowed identifying spinoff founders. Likewise, given that the target population of GEM consists of all adults aged 18-64, and not just employees as my work requires, I have added additional questions to identify those being recently in paid-employment. Specifically, the identification of entrepreneurs and employees has been done following the set of 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 have been defined as entrepreneurs.
- Employees have been defined 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.

Table A.1: Description of the questionnaire

Entrepreneurs
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. In all other cases the options include: Yes/ No/ Don't know/ Refused.

Those individuals being categorised in any of these target groups have also answered further questions related to their current or most recent employer characteristics, such as industry, firm size and location. The full version of the extended survey (including screening questions and follow-up questions) has gone through a revision and approval of the GEM Global Research Committee.

Appendix B

Appendix Chapter 4

B.1 Explaining Employee Mobility

Table B.1: Determinants of the hazard of turnover

	Turnover probability	
Firm size:1-9	0.824***	(0.01)
Firm size:10-19	0.567***	(0.01)
Firm size:20-49	0.422***	(0.01)
Firm size:50-249	0.220***	(0.01)
Unemployment	-0.011***	(0.00)
Firm age	-0.005***	(0.00)
Job market experience	-0.034***	(0.01)
Firm tenure	0.275***	(0.00)
Skilled	-0.575***	(0.02)
Unskilled	0.275***	(0.01)
Full time	-0.588***	(0.01)
Permanent	-0.805***	(0.01)
Age	0.030+	(0.02)
Dismissed	3.475***	(0.01)
Observations	2,748,055	
No. groups	187,228	
Pseudo R^2	0.345	

Note: Coefficients; Standard errors in parentheses. It also controls for quarter, industry and year-industry fixed effects.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.2 Construction of the Dataset

The "Muestra Continua de Vidas Laborales" (MCVL) consists of eight different files from which three of them are used in this study: 1) AFILANON which contains the core information to build the dataset on the employment relationships and employer characteristics and is collected from the Social Security records; 2) PERSANON which provides data on individual demographics and is obtained from the population census and 3) DATOS_FISCALES that allows matching with personal income-tax data provided by the Tax Agency. The latter are not available for the Basque Country and Navarre where they have competence over collecting and administrating their taxes. Individual related files can be matched through an identification code, in the same manner that employers social security codes are shared though files containing any information about firms. In fact, each firm has at least two social security numbers; a principal number and a secondary number, or a series of them to reflect multiple plants, for example.

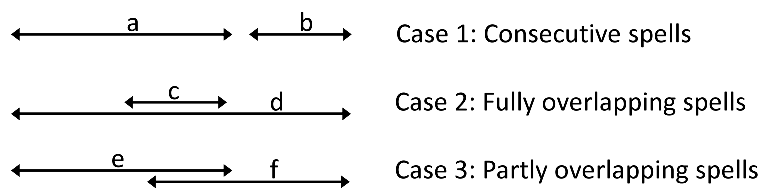
One of the drawbacks of using the dataset is its administrative origin and therefore necessary effort in cleaning and preparing to conduct any analysis. In fact, many variables have a large number of missing values when they are not compulsory to fill in, such as county of birth, or they are not updated as soon as the change occurs or even not changed at all. For instance, educational attainment, which is obtained from the population census, seems to be biased downwards as citizens do not tend to notify upgrades, in particular when they reside at the same home address (Lapuerta, 2010; García, 2008).

But more importantly, the longitudinal or dynamic analysis of the data requires reshaping the original data that comes in the form of a series of spells that correspond to all employment relationships that each individual has into the panel form ("episode splitting"). This implies defining individuals, rather than employment spells, as the unit of analysis but requires handling with the fact that on average, each individual holds around 12 different labour relationships through his/her career (García, 2008) which are simultaneous in many cases.

Based on Arranz and García-Serrano (2011), Durán (2007), García (2008), Lapuerta (2010) and the documents provided by the Spanish Social Security Agency I have followed the next steps to create the current version of the dataset:

1. As said converting original data into the panel structure allows having one event or working relationship per unit of time, while in practice more than one relationship can occur simultaneously as the result of situations of multiple employment or multiple activity as presented in figure B.1. The first case corresponds to the easiest case that requires no adjustment, where contracts take place sequentially and the time left between a and b is a period of unemployment or inactivity. In the second case, the job spell c starts and finishes before the previous spell d ends. I have removed these kinds of spells from the dataset. Finally, when jobs are partly overlapped as in case 3, a primary occupation needs to be defined in order to postpone the registration date of spell f or to move the cancellation date of spell e forward instead. To do so, I have taken permanent jobs as opposed to temporary jobs as principal contracts. If they were of the same type I have chosen the longest spell. And thirdly, when these conditions were identical for both contracts I have selected the job with the earliest registration date.

Figure B.1: Simultaneous spells in the MCVL



Source: García (2008)

2. A number of variables related to job experience (tenure in the firm and labour market experience) are created. These sum up the working days in the firm and in the labour market since the first appearance in the dataset, and therefore, the first relationship with the Social Security. Employment spells that ended before 2005 are

then deleted and the dataset is reshaped into the long form before merging all yearly waves together. Due to time varying covariates it is necessary to start building the dataset from the oldest wave of the data and to add new spells and individuals on it, otherwise older information would be replaced by the most current data. That is, even if 2010 files contain the lifetime working histories for all individuals in the sample in 2010, for both who remain in the sample and those introduced in the sample for the first time and therefore have Social Security records only in 2010, time varying variables, such as firm size or city of residence, refer to the state in 2010 while these have probably changed from previous years.

3. Given that for each employment relationship the starting and ending dates of the contract are provided, this makes possible to convert it into up to a daily frequency panel, although in practice this would be extremely memory intensive. Following Fersterer *et al.* (2008) I define quarterly cutting points every year on February 10, May 10, August and November 10 (24 quarters in total) and select the employment relation that is active at each of these points in time. Of course, this leaves out employment relations that may occur within the cutting points and are too short to be observed.

4. Finally the rest of the files are matched with the above master dataset. In the case of Income Tax data, individual and firm identification codes are used to match earnings in each firm and year. For each contract I compute an equivalent daily salary based the duration of the contract in the respective firm and year. I also correct for a part time coefficient (expressed in percentages) provided in the original affiliation file and I adjust for inflation using the annual Spanish consumer price index of the corresponding fiscal year. Using the province of residence (which is equivalent to the NUTS-3 level) given by the population census data unemployment rates are matched as well. These are obtained from the Economically Active Population Survey ("Encuesta de Poblacion Activa") compiled by the Spanish National Statistics Office (INE) and collected at the province level on quarterly basis.