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Essays in Employee Entrepreneurship

THESE

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Résumé général en français

Cette dissertation est composée de trois essais sur l'entrepreneuriat de l'employé. Les trois essais analysent les antécédents d'entrepreneuriat de salarié dans lesquels les individus ont quitté un emploi rémunéré pour monter leur propre entreprise. Dans le premier essai, j'étudie pourquoi, historiquement, les firmes les plus performantes (comme Apple et IBM) ont généré plus d'entrepreneurs que les autres. Afin de répondre à cette question, je construis deux argumentations appelées *faire un tri dans le marché du travail* et *apprendre au sein de l'entreprise de référence* dans le but d'en faire un modèle rationnel qui prédirait indépendamment le départ des employés vers l'entrepreneuriat. La première argumentation met l'accent sur les aptitudes individuelles alors que la seconde se focalise sur les opportunités d'apprentissage qui se trouvent être meilleures dans les entreprises les plus performantes. Ces deux retombées seront mêlées lors du classement fait dans le marché du travail où les meilleurs individus avec les meilleures capacités observables se trouvent dans les firmes de plus grande qualité. En utilisant un modèle simple de principal-agent avec une asymétrie d'information, je crée trois prédictions testables sur l'esprit d'entreprise et l'aboutissement des individus dans le marché du travail. Le modèle génère les prédictions suivantes : A) une homogamie existe dans le marché du travail, B) les salariés de firmes de haute qualité changent moins de firmes, C) la probabilité d'entrepreneuriat augmente avec la qualité de la firme qui emploie, D) la probabilité d'entrepreneuriat augmente avec les capacités de l'individu. Ces propositions m'aident à tester de façon empirique les deux opinions opposées concernant l'esprit d'entreprise du salarié. Les premiers défenseurs des retombées contextuelles sur l'esprit d'entreprise des salariés avancent que les meilleures firmes sont de précieux stocks de savoirs et d'opportunités dont les employés peuvent tirer profit pour monter leur propre entreprise.

Dans le deuxième essai, j'examine le lien entre l'appariement dans le marché du travail et les transitions des employés d'un travail rémunéré à l'entrepreneuriat. La théorie de l'appariement dans l'économie du travail n'est pas élaborée à partir des résultats des employés sur le marché ignorant alors le taux de renouvellement des employés et leur rémunération brute. Pour comprendre

parfaitement les conséquences de l'appariement sur les résultats des employés dans le marché du travail, j'ai intégré l'entrepreneuriat au processus de rotation. En utilisant un modèle reconnu, je montre que la combinaison de qualités influe sur la transition de l'emploi salarié à l'entrepreneuriat au travers de deux mécanismes : l'apprentissage de savoir-faire spécifiques et la limitation des opportunités pour l'avancement dans le marché du travail. Je montre en particulier que les employés à capacité d'appariement élevée et faible s'orientent vers l'entrepreneuriat en comparaison aux employés à capacité d'appariement modérée. Les premières formes de croissance se tournaient vers les produits dérivés alors que les dernières classaient seulement les créateurs-proprétaires d'entreprises.

En ce qui concerne l'analyse empirique des deux premiers essais, j'utilise un ensemble de données suédois étonnamment riche. Cet ensemble de données longitudinal englobe l'ensemble des individus et des firmes suédois de 1985 à 2009. La combinaison de données me permet de suivre l'historique de la carrière des individus en remontant dans le temps et de construire un échantillon sur la mobilité des individus au long de leur carrière, ce qui est une fonctionnalité importante pour faire des recherches, trier et associer. Dans le cadre empirique, j'utilise une méthodologie novatrice afin d'estimer la qualité individuelle, la qualité de la firme et associer les qualités suivant la décomposition des conséquences fixées. J'utilise ensuite ces conséquences prévues pour une régression de la mobilité et de l'esprit d'entreprise pour analyser les relations entre l'association et le tri avec la probabilité d'entrepreneuriat. Mon analyse préliminaire suggère que, en effet, le marché du travail range les employés de grande qualité dans des firmes de grande qualité. Les employés de firmes de grande qualité ont plus de chance de connaître une transition vers l'entrepreneuriat que ceux des firmes de faible qualité. Les employés de grande qualité ont plus de chances de connaître une transition vers l'entrepreneuriat. Finalement, l'appariement n'a pas de conséquence linéaire sur la probabilité de transition vers l'entrepreneuriat. Je trouve, en particulier, que, aussi bien les employés mal associés que les employés avec une association de grande qualité transitent d'un emploi salarié vers l'entrepreneuriat, comparé aux employés modérément associés. Le type de transition vers l'entrepreneuriat en U que l'on peut observer est expliqué par le taux de transition plus élevé vers l'auto-entreprise parmi les employés mal répartis et le taux plus élevé de transition vers des SARL de

produits dérivés parmi les employés bien associés. Ce qui plus est, la probabilité de voir apparaître des produits dérivés au sein de l'industrie et des équipes entrepreneuriales augmente avec la qualité de l'appariement. Ces résultats sont des compléments intrigants à la littérature sur le marché du travail et le renouvellement. Potentiellement, ils pourraient également éclairer un aspect obscur, celui de l'appariement selon la perspective des firmes.

Dans un troisième essai, j'examine les conséquences de l'investigation et l'exploitation organisationnelle sur l'entrepreneuriat du salarié. Cet essai est motivé par le manque d'attention que la théorie organisationnelle et la littérature instructive sur l'organisation portent à des micro-conséquences comme le taux d'emploi et les réussites entrepreneuriales des employés. Par rapport aux recherches antérieures qui affirment que le stock de connaissances d'une organisation crée une série d'opportunités dont les employés peuvent tirer profit afin de s'ouvrir de nouveaux horizons, je prend du recul et me demande comment la manière dont la connaissance est générée au sein des organisations affecte la création entrepreneuriale des employés. J'examine en particulier les liens entre la production de connaissances en stratégie des organisations par le biais de l'exploration (au sein et à travers des domaines de connaissance) et la création entrepreneuriale. J'intègre l'apprentissage organisationnel et la littérature novatrice par la littérature entrepreneuriale pour développer une structure théorique qui explique les micro-conséquences de l'exploration organisationnelle sur le départ des employés pour l'entrepreneuriat. Mon argument est que ce n'est pas simplement le stock de connaissances qui donne des opportunités entrepreneuriales aux employés mais c'est la structure des connaissances de base (qui est créé par des moyens d'exploration et d'exploitation) qui affecte une série d'opportunités vacantes, la motivation des employés des entreprises de produits dérivés à trouver leurs propres entreprises. Pour l'analyse empirique, je construis une base de données prenant les informations pertinentes de la base de données Venture Source (anciennement Venture One), la base de données populaire Capital IQ, COMPUSTAT et la base de données reconnue de NBER. Je teste le modèle théorique grâce à un échantillon de firmes de l'industrie des appareils médicaux dont le commerce est public entre l'année 1985 et l'année 2006. Les résultats de mes analyses suggèrent que l'exploration au sein des domaines de connaissances

existant des firmes inhibe la création d'entreprise alors que l'exploration à travers de nouveaux domaines de connaissance augmente la probabilité de création d'entreprise. Cette découverte intrigante suggère que la série d'opportunités vacantes de laquelle les employés peuvent tirer profit pour créer leur propre entreprise est définie par l'ajustement entre les connaissances nouvelles et les atouts complémentaires de la firme afin d'utiliser ces connaissances en interne.

1 Introduction

This dissertation is comprised of three essays on employee entrepreneurship. All three essays examine the antecedents of employee entrepreneurship where individuals leave paid employment to form their own business. In the first essay I examine why historically best performing firms (e.g. Apple and IBM) generate more entrepreneurs than other firms. To answer this question I build two processes namely *sorting in the labor market* and *learning within the incumbent firm* into a formal model that would independently predict departure of employees to entrepreneurship. The former process emphasizes individual abilities whereas the later emphasizes better learning opportunities at best performing firms. These two effects will be confounded through sorting in the labor market where best individuals with better observable abilities sort into qualitatively better firms. Using a simple principal-agent model with information asymmetry I produce four testable predictions on entrepreneurship and labor market outcome of individuals. The model generates following predictions: *A*) positive assortative matching exists in the labor market, *B*) employees of high quality firms are less likely to switch firms, *C*) the likelihood of entrepreneurship increases with the quality of the employing firm, and *D*) the likelihood of entrepreneurship increases with the ability of the individual. Empirically these propositions help me test two opposing views on employee entrepreneurship. First advocates of contextual effects on employee entrepreneurship argue that best firms are valuable repositories of knowledge and opportunities on which employees can tap on to start their own business. On the other hand two-sided matching logic suggests that labor market (ideally frictionless) sorts best employees into best firms and therefore the entrepreneurial spawning of employees may also be attributed to this two-sided matching process beyond any learning from the employing firm.

In the second essay I investigate the relationship between matching in the labor market and the entrepreneurial transition of employees from paid work. Matching theory in

labor economics does not elaborate on the labor market outcomes of employees beyond turnover and wage growth. To completely understand the consequences of matching on the labor market outcomes of employees I embed entrepreneurship into the turnover process. Using a formal model I show that match quality affects entrepreneurial transition from paid employment through two mechanisms: learning specific skills and limited opportunities for advancement through the labor market. In particular I show that employees with high match quality and low match quality transition to entrepreneurship compared to moderately match employees. The former forms growth oriented spinoffs whereas the latter sorts into founding sole-proprietorship businesses.

For the empirical analysis in the first two essays I use an unusually reach employer-employee matched dataset from Sweden. This longitudinal dataset covers all the population of Swedish individuals and firms from 1985 to 2009. The matched dataset lets me track individuals' career histories back in time and enables me to construct the mobility pattern of individuals throughout their career, an important feature for investigating sorting and matching. In the empirical setting I use a novel empirical methodology to estimate individual quality, firm quality, and match quality based on the decomposition of the fixed effects. I then use these estimated effects in a mobility and entrepreneurship regression to investigate the relationship between matching and sorting on the likelihood of entrepreneurship. My preliminary analysis suggests that indeed labor market sorts high quality employees into high quality firms. Employees of high quality firms are more likely to transition to entrepreneurship than employees of low quality firms. High quality employees are more likely to transition to entrepreneurship. And matching has a nonlinear effect on the likelihood of transition to entrepreneurship. In particular I find that both mismatched employees and employees with high match quality transition to entrepreneurship from wage work compared to moderately matched employees. The observed U-shape type transition to entrepreneurship is explained by the higher transition rate to self-employment among mismatched employees and higher transition

rate to incorporated spinoffs among well matched employees. In addition, the likelihood of intra-industry spinoffs and team entrepreneurship increases with match quality. These results are intriguing additions to the literature on matching and turnover and potentially highlights a dark side to matching from the perspective of firms.

In a third essay I investigate the effect of organizational exploration and exploitation on employee entrepreneurship. This essay is motivated by the lack of attention of organizational theory and organizational learning literature on micro-consequences such as employment and entrepreneurial outcomes of employees. In contrast to past research that argues that an organization's stock of knowledge creates an opportunity set on which employees can tap on to found new ventures, I take a step back and ask how the way that knowledge is generated inside organizations affect entrepreneurial spawning by employees? In particular I investigate the relationship between knowledge generation strategies of organizations by means of exploration (within and across knowledge domains) and entrepreneurial spawning. I integrate organizational learning and innovation literature with entrepreneurship literature to develop a theoretical framework that accounts for micro consequences of organizational exploration on entrepreneurial departure of employees. I argue that it is not merely the stock of knowledge that gives entrepreneurial opportunities to employees but it is the structure of the knowledge base (that is created by means of exploration and exploitation) that affect idle opportunity set, and the motivation of employees to spin-off to found their own ventures. For the empirical analysis I construct a database by extracting relevant information from Venture Source (previously Venture One) database, Capital IQ's people intelligence database, COMPUSTAT, and NBER's patent database. I test the theoretical model with a sample of publicly traded firms in the medical devices industry from 1985 to 2006. The results of my analysis suggest that exploration within existing knowledge domains of the firm inhibits entrepreneurial spawning whereas exploration across new knowledge domains increases the likelihood of entrepreneurial spawning. This intriguing finding

suggests that the idle opportunity set on which employees can tap on to start their own business is shaped by the fit between the new knowledge and firms' complementary assets to use that knowledge internally.

2 Essay One: Selection vs. Learning

2.1 Introduction

New firms are often created by individuals leaving paid employment at some point during their career (Bhide, 2000)¹. The evidence is widespread in many industries such as semiconductors (Braun and MacDonald, 1982; Brittain and Freeman, 1986), disk drives (Christensen, 1993; Agarwal et al., 2004), lasers (Klepper and Sleeper, 2005), biotechnology (Mitton, 1990; Stuart and Sorenson, 2003), medical devices (Chatterji, 2008), automobiles (Klepper, 2007), and in professional services sectors such as management consulting or legal industry (Phillips, 2002). It therefore seems reasonably safe to say that “firms are born out of existing firms”. However not all firms are equal in the rate of spin off generation. Some firms are hot beds of entrepreneurship from which employees spin off disproportionately more than other firms to start their own business (Sørensen and Fassiotta, 2011). For example Klepper and Sleeper (2005), Gompers et al. (2005), and Agarwal et al. (2004) report that, all else equal, technologically advanced firms are more likely to generate spin offs than other firms. Steven Klepper in a series of works (Klepper, 2007, 2009a) analyzing spin offs in semiconductor industry and automobile industry suggest that leading firms in the industry are more likely to generate spin offs.

Theoretically a dominant explanation for the observed difference among firms in the rate of spin off generation has been attributed to firm quality and the superior learning environment (e.g. skills and entrepreneurial opportunities) that some firms provide to their employees (Klepper, 2009a; Franco and Filson, 2006). This theoretical view is limited because the same firm quality attributes may also lead to sorting of best workers, who may eventually spin off, into high quality firms (Abowd et al., 1999). This back end sorting of best employees into high quality firms therefore confounds the real effect of learning from the employing firms. A theory of entrepreneurial spawning

¹The terms “spin off” or “spin out” are often used (interchangeably) in the literature to describe this phenomenon.

should therefore account for individual ability and the back end labor market sorting of employees. In this chapter I develop a formal model that does exactly this by accounting for the interaction between individual ability and firm quality. Empirically I disentangle the confounding effect of individual ability on firm quality that arises from sorting in the labor market.

The model is a simple principal-agent type with two principals (firms) and one agent (worker). In the start worker is assigned randomly to one of the agents to produce with its technology. The principals' technology has a quality grade and the worker has an ability level both of which are private information to the parties before the employment contract. Upon employment the parties involved in the contract learn about each others' quality. In addition the worker learns how to produce with the technology of the employing firm (the inside firm) and can absorb the technology to start his own business or to move to another firm (the outside firm) to produce with its technology. The main assumption of the model is that the inside firm and outside firm differ in their information about the quality of the worker and therefore differ in their wage policies. The details of these assumptions are discussed in the next section.

The main features of the model are summarized as follows. Having full information about the worker quality, the inside firm adapts a continuation wage policy that depends on the worker's outside option to start a competing firm using its technology. On the other hand, having no information about the quality of the worker, the outside firm sets a rigid (cut off) wage policy to potentially lure away the worker from the inside firm. The dynamics of the outcome for the worker depends on the quality of her employer, the quality of the other employer, and her own ability to produce with the technology grades of the inside firm and the outside firm. The model predicts that returns to entrepreneurship increases with the quality of the employing firms as well as the ability of the worker. This is because of the complementarity of the worker ability and firm's technology in the production function. Workers employed at high quality firms do not

switch firms. In addition better workers sort into better firms although they may not be informed of the quality of the employing firm ex-ante.

In the empirical section I use a novel employer-employee linked database from Sweden to investigate the predictions of the model. I obtain results that are consistent with the predictions of the model. The econometric specification employs a novel fixed effects methodology to decompose the quality of the worker and firms.

2.2 Theoretical Model

Consider an economy consisting of two types of agents, workers and firms, of which there are many². Firms in this economy differ in their quality. Denote the quality of the firm by $q > 1$ which is uniformly distributed with the support on $[1, \bar{q}]$. \bar{q} denotes the highest firm quality. We consider firm quality as a specific attribute that is directly related to its production output. Idiosyncratic technologies, complementary assets such as existing human capital, or even reputation can represent firm quality. Workers also differ in their quality. Denote worker quality by $x > 1$ with the cumulative distribution $G(x)$, density $g(x)$, and support on $[1, \bar{x}]$. \bar{x} denotes the highest worker quality. The worker is risk neutral with reservation utility $\underline{U} = 0$.

The timing of the model is as follows. The model starts at time zero where a worker is randomly assigned to one of the two firms. Denote the focal employer of workers as *inside firm* with quality q_i and the other employer as *outside firm* with quality q_o .

Now given the above assumptions I continue to period one. In period one the worker receives an update about the value of her human capital, x . Once revealed the firms receive a signal $s \in S$ about the value of the worker's human capital. I assume that the inside firm receives complete information about worker quality, $s = x$, whereas the outside firms receive an unknown signal. Based on s the inside firm decides on the wage schedule $B(s)$ for the worker. Because of the complete information assumption the inside

²The number of workers and firms is irrelevant as long as there are enough workers and firms to establish a clear ranking.

firm's wage schedule is a continuation wage offer.

The agent compares the inside firm's wage offer with her outside utility from leaving the inside firm. In case of leaving the worker would have two options, either to move to another employer or start her own business. whether to stay with the inside firm, to move to the outside firm, or to become entrepreneur depends on the utility that she obtains from each alternative. Accepting the wage offer gives the firm $x - B$.

Since I introduced entrepreneurship as a viable choice for the worker I will explain its utility function below. If the worker rejects both the offer of the inside firm and the offer of the outside firm, she will become entrepreneur with the entrepreneurial pay-off denoted by $U(q_i, x, \cdot)$,

$$U(q_i, x) = xq_i - c \tag{2.1}$$

In the above equation, the parameter c represents the sum of the financing cost of starting a business and the private benefits to entrepreneurial activity. Similar formalization of the parameter c is also used in Hvide (2009). An important feature of the worker's entrepreneurial utility is *increasing returns* to her human capital with respect to the technology of her employer. The reason for the technology of the worker's employer to enter into the entrepreneurial utility function is to capture the *learning* of the employer's technology. This intends to capture the dominant theoretical logic of spinout formation where employees inherit knowledge (both technical and non-technical) from their employers (Agarwal et al., 2004; Klepper and Sleeper, 2005; Franco and Filson, 2006). Knowledge inheritance also implies that the more technological advanced the parent firm is the more technologically advanced its spinout firm will be (Agarwal et al., 2004), and hence the spinout's productive output.

Inside firm's wage schedule

The inside firm, by assumption, has complete information about the value of the workers' human capital upon its realization in period one. Therefore the inside firm receives a signal $s = x$. Complete information allows the inside firm to offer a piece rate wage contract to the worker based on the productivity output of the worker with the technology of the inside firm. The worker therefore will be compensated according to her productive output, $B_i = \alpha x q_i$. The parameter $\alpha \in (0, 1)$ intends to capture the share of the production output that the worker keeps. There is no straight forward way to determine this division of value and it is usually determined by a complex bargaining problem (Kremer, 1993). We assume that all the firms in the economy have the same rent sharing rule. It should be noted that α never equals 0 or 1 in a production coalition otherwise forming the coalition is infeasible. However, the worker can keep all the value of her production output by forming a spinout firm, in such a case $\alpha = 1$. In general the inside firm's optimum wage offer given the entrepreneurial utility of the worker will be,

$$B_i^* = \begin{cases} 0 & \text{if } U(q_i, x) > \alpha x q_i \text{ or } U(q_i, x) < 0 \\ x q_i - c & \text{if } 0 < U(q_i, x) < \alpha x q_i \end{cases} \quad (2.2)$$

Equation (2) illustrates that the inside firm compensates the worker according to her productive output if the worker's entrepreneurial utility falls below her realized value of productive output. Such a drop in entrepreneurial utility below her value of human capital occurs when there are significant costs to entrepreneurship. In addition the worker leaves when $U(q_i, x) = x q_i - c > \alpha x q_i$ meaning that when $x > \frac{c}{(1-\alpha)q_i} \equiv P$. Differentiating P with respect to q_i we obtain,

$$\frac{\partial P}{\partial q_i} = \frac{-c}{(1-\alpha)q_i^2} < 0 \quad (2.3)$$

This implies that the utility from entrepreneurship increases with the quality or the technology of the inside firm since the required threshold P decreases with q . As the threshold P decreases the likelihood that x is greater than P increases and therefore more workers will become entrepreneurs ³. In addition this means that even workers with low value of human capital will become entrepreneurs if they are employed in firms with sufficiently high quality. Therefore following proposition can be made regarding spin-out formation,

Proposition 1: *The likelihood of entrepreneurship increases with q .*

The symmetry between x and q in the entrepreneurial utility means that the similar proposition can be formed with respect to the quality of workers. Therefore,

Proposition 2: *The likelihood of entrepreneurship increases with x .*

Outside firms' wage schedule

By assumption the outside firm does not receive a precise information about the value of the worker's human capital but instead knows the distribution of worker's human capital, $g(x)$. As a result the outside firm can not adopt a continuation wage schedule to the worker upon hiring her. This will result in setting a cut-off wage offer that would lure away some of the workers from the inside firm. The outside firm's optimal wage offer is denoted by B_o^* . Given an offer $B_o \geq 0$ the worker is lured away if $B_i < U(q_i, x) = xq_i - c \leq B_o$, or in other words if x does not exceed the cut-off z , where

$$z = \frac{B_o + c}{q_i} > \frac{B_i + c}{q_i} \tag{2.4}$$

³Because x is a random variable with a uniform distribution over the support $[1, \bar{x}]$, a lower threshold within the support increases the likelihood that a new draw of x falls above the threshold.

Taking the cut-off z as a choice variable for the outside firm to maximize its profits with respect to the worker's best response which is her entrepreneurial utility $U(q_i, x)$, the outside firm's profit equals

$$\Pi_o = \int_0^z (xq_o - zq_i + c)g(x) dx. \quad (2.5)$$

In other words the outside firm's problem is to find the argument of the maximum of the above profit function. This would result in the optimal cut-off z^* ,

$$z^* = \arg \max_{z>0} \left\{ \int_0^z (xq_o - zq_i + c)g(x) dx \right\}. \quad (2.6)$$

To find the cut-off z we take the first order derivative of Π_o with respect to the parameter z . Following the Leibniz integral differentiation rule we obtain,

$$\Pi'_o = (zq_o - zq_i + c)g(z) - q_iG(z). \quad (2.7)$$

Existence of a maximum requires that the second order condition of the profit function be negative, this implies that the z^* should satisfy the following,

$$\Pi''_o = (q_o - 2q_i)g(z^*) + (z^*q_o - z^*q_i + c)g'(z^*) < 0. \quad (2.8)$$

The above equations reflect the outside firm's trade-off when choosing the cut-off wage z . The greater the cut-off wage is the more is the number of workers lured away from the inside firm and the more would be the overall wages offered to all types of employees that are lured away. Setting a cut-off wage means that there will always be some employees from the inside firm that join the outside firm and some employees that reject the wage offer of both the inside firm and the outside firm. Those employees who reject the outside firm's wage offer are the ones with higher value of human capital

because they are drawn from the top the distribution of x since $U(x)$ slopes upward in x . These employees will therefore spin-out and become entrepreneurs. Assuming the existence of a unique solution to Π'_o , the parameter z can be written as the differentiable function of q_i , q_o , and c , namely $z^*(q_o, q_i, c)$. Now to get the comparative statistic relationships it is enough to implicitly differentiate the equation (5) with respect to the parameters q_i , q_o , and c . Therefore we would obtain,

$$\begin{aligned}\frac{\partial z^*}{\partial q_o} &= -z^*g(z^*)/\Pi''_o > 0. \\ \frac{\partial z^*}{\partial q_i} &= z^*g(z^*) - G(z^*)/\Pi''_o < 0. \\ \frac{\partial z^*}{\partial c} &= -g(z^*)/\Pi''_o > 0.\end{aligned}\tag{2.9}$$

Above comparative statistics show the following results. First, with respect to the technology of the inside firm, the marginal cut-off wage of the outside firm decreases with q_i . Intuitively this means that increased quality of the inside firm makes the marginal employee less valuable to the outside firm and as a result the number of the employee that would join the outside firm will decrease. Second, regarding the technology of the outside firm, the marginal cut-off wage of the outside firm increases with q_o . This means that to benefit from the complementarity between the technology of the firm and the value of the human capital of the employees the outside firm would increase the cut-off wage in order to attract better employees from the inside firm. In other words firms with higher technology benefit from the marginal employee that they can lure away from other firms. Regarding the parameter c , increase in entrepreneurial costs makes the marginal employee more valuable for the outside firm since the increase in the cut-off wage would allow the outside firm to obtain higher quality employees from the inside firm. In general the above comparative statistics results in the following propositions,

Proposition 3: *There exists positive assortative matching between employees and firms (based on $\frac{\partial z^*}{\partial q_o} > 0$).*

Proposition 4: *Employees of high quality firms are less likely to switch firms (based on $\frac{\partial z^*}{\partial q_i} < 0$).*

2.3 Data and Sample Construction

Data for the empirical analysis comes from two matched longitudinal data sources from Sweden. The first is the longitudinal integrated database for medical insurance and labour studies (LISA) and the second is the firm financial statistics database (Företagens ekonomi (FEK)). Both databases are maintained by Statistics Sweden.

LISA is a large database of all the population of Swedish individuals who are 16 or older. The LISA database is constructed by pooling multiple governmental registers. The primary focus of the LISA database is individual, but it also links individuals to family, businesses and workplaces. Although the primary focus of the LISA database is the individual but it is the individual object that defines the population and various individual information can be aggregated to obtain data at the level of the population. The LISA database currently contains vintages from 1990 to 2009 and includes all the individuals whose age is 16 and older and who were registered in Sweden as of December 31st of each year. Statistics Sweden (SCB) maintains LISA and uses LISA to produce statistics on education, labour as well as statistics on persons outside of the labour market. The purpose of creating LISA by Statistics Sweden is to pool together and make better use of existing register data on individuals' relation to labour market and employment as well as their health and insurance. The LISA database complements the traditional labour market statistics and provides a better description of the labour and people's relationship to the workplace and the individual's life situation. The longitudinal nature of LISA enables data for a single person to be linked together for all years

that the person is registered in Sweden and currently data on each person can be traced back up to 20 years.

LISA is constructed by pooling information from the following sources: register based labour market statistics (RAMS), register of education, register of immigrants (SFI), total population register (RTB), income and tax register (LOT), population and housing census, and the business survey. Variables in LISA are mainly grouped in as: demographic variables, educational variables, employment variables, income variables, family variables, and workplace/firm variables.

FEK is a firm financial information database which is based on the survey of all the business in Sweden for tax purposes. The purpose of the FEK database is to highlight the business (excluding the financial sector) structure with respect to profitability, growth, development, financing and production. FEK is conducted annually and the complete information for all business is available from 1997 onwards. Firms in FEK are identified with a unique identification number which makes it possible to link FEK with other database such as LISA. Such integration will let individuals to be matched with firms and the individual information to be connected with the firm level information.

The Swedish employer-employee matched data has recently been used by management scholars to study entrepreneurship (Giannetti and Simonov, 2009; Folta, Delmar, and Wennberg, 2010; Delmar, Wennberg, and Hellerstedt, 2011), productivity effects of mergers, acquisitions, and corporate restructuring (Siegel, Simons, and Lindstrom, 2005; Siegel and Simons, 2010).

Sample Construction

The extract of the LISA database available to me starts in 1986 and ends in 2008. For the analysis I use the panels from 1990 to 2007. The reason to start the panel in 1990 was mainly because of using the prior panels to calculate several measures that required historical information such as tenure in 1990. I chose to end the panel in 2007 in order to observe the mobility of the individuals at the end of the panel. To do this I utilize the

information from the 2008 extract of LISA. In addition I limit the analysis to individuals whose age is between 20 and 60 during the sample period to avoid non-random attrition due to retirement. I drop firms active in the health, education, agriculture and fishing industries, and also firms in the public sector, in order to focus on private sector firms. I follow the definition used by Statistics Sweden to define entrepreneurs. Statistics Sweden defines an individual as being employed in her own firm in a given year if her total income from her own company (labor and capital income) is greater than 62.5 percent of all other labor income.

2.4 Variable Description

Dependent Variables

Entrepreneurship. I define entrepreneurship when an employee leaves paid employment to start a new incorporated firm. Hence the variable takes a value of 1 when an employee founds a new firm in the period immediately after paid employment and zero if the employee continues to be employed with her focal employer. It should be noted that I code entrepreneurial transition when the following conditions are simultaneously met: 1) An individual is classified by Statistics Sweden as working in her own company in the subsequent year, but had not been in the current year. 2) The individual's future firm identifier is different from the current identifier. 3) The future firm identifier has never appeared in the data before the transition.

Mobility. I define mobility when an employee switches firms between two consecutive periods. Hence the variable takes a value of 1 when an employee moves to another established firm in the subsequent period and zero if the employee continues to be employed with her focal employer. This variable excludes entrepreneurship.

Independent Variables

Firm Quality. The theoretical model predicted that individuals working in high quality firms are more likely to become entrepreneurs than employees of low quality

firms. I assume that firm quality is a stable characteristic of the firm that does not vary over time. I measure firm quality with firm fixed effect. The details of the measure is described in the methodology section.

Individual Quality. The theoretical model predicted that high ability individuals are more likely to transition to entrepreneurship than individuals with low ability. I measure individual ability with individual fixed effect from the wage regression. The details of the measure is described in the methodology section.

Control Variables

Tenure. The variable “tenure” captures the cumulative employment duration of employees at the parent firm in each year. Theoretical and empirical works in labor economics (Jovanovic, 1979; Topel and Ward, 1992) show that turnover is decreasing with the tenure of workers.

Age. Another highly related variable to turnover and entrepreneurship is age. Age is consistently shown to be negatively related to worker turnover (Viscusi, 1980; Stumpf and Dawley, 1981). Regarding entrepreneurship the percentage of self employed individuals rises with age until around 45 and then remains constant until 60 and rises again sharply (Evans and Leighton, 1989).

Female. This variable takes a value of 1 for females and zero for males. Job quit rate as well as the rate of entrepreneurship are shown to be different among males and females. In general females exhibit more job quit rates than their male counterparts (Viscusi, 1980; Loprest, 1992) and are less likely to become entrepreneurs than men (Blanchflower and Oswald, 1998). The job quit pattern of females and males might be related to the type of jobs that they chose to work (Viscusi, 1980). Therefore I control for the possible correlation of gender differences and the type of firms that they chose to work.

Education. Educational attainment of individuals is likely to be correlated with the type of job and company that they work. Educational attainment is therefore a means of

selection in the labour market (Spence, 1973) for employers. Education is also shown to be related to turnover and mobility of workers Buchinsky et al. (2010). I create 4 dummy variables for educational attainment corresponding to the years in school: less than or equal to 11 years ($Education \leq 11$), equal to 12 years ($Education = 12$), between 12 and 15 years ($Education > 12, \leq 15$), and greater than 15 years of schooling ($Education > 15$).

Swedish background. This variable is a dummy variable that takes a value of 1 if the individual was born in Sweden with at least one Swedish born parent. It takes a value of 0 for individuals born outside of Sweden or born in Sweden from two foreign parents.

Firm Age. This is a firm level variable that measures the age of the employing firm. Actual value of firm age is not available in the Swedish micro data, therefore I create a proxy that counts the number of years since the first time the firm appears in the data. The first panel of Swedish micro data starts in 1985 therefore the actual age of very old firms is left censored. The maximum value of firm age proxy is 22 years.

Employer's Nr. of Employees. This variable is a proxy for firm size and is measured by counting the number of employees for each firm in each time period.

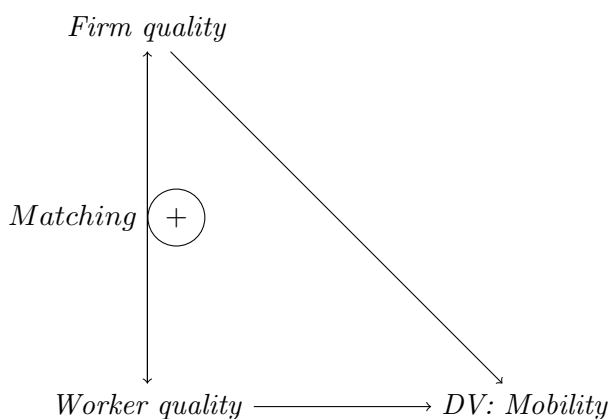
Nr. of Establishments > 1. This variable is to distinguish between multi establishment firms and single establishment firms. It is a dummy variable that takes a value of 1 if a firm has more than one establishment and 0 if the firm has only one establishment.

2.5 Methodology

As shown in the theoretical section the complementarity in production implies that higher quality workers sort into high quality firms. This sorting pattern resembles the kind of sorting that is observed in two sided matching models (Gale and Shapley, 1962; Roth and Sotomayor, 1992) ⁴.

⁴Gale and Shapley (1962) first analysed the two-sided matching process in a college admission model. In the original formulation of Gale and Shapley's college admission model, students have preferences over colleges and colleges have preferences over students as well and the outcome is the observed matches

Empirically, in econometric analysis of two-sided labor market, potential existence of assortative matches between workers and firms biases the estimates of the effects of supposedly exogenous variables of the structural model (Sorensen, 2005). These variables become endogenous because of the way they are paired together in the data. Because high quality workers and high quality firms are likely to be matched together in equilibrium the two-sided selection bias occurs in the data. Following graph illustrates the nature of the bias. Therefore empirical strategies used to estimate the parameters of structural models in two-sided markets should carefully consider the *two sided selection bias* arising from assortative matchings.



If worker quality and firm quality were perfectly measurable and they were perfectly observed in the data, the econometrician could easily eliminate the bias by including them in the structural model. However when the dimension of quality for both (or either of) workers and firms is unobserved in the data, sorting causes bias. Essentially

between students and colleges. Gale and Shapley introduced the concept of *stability* in matches and proved that under the specified assumptions there would always be a stable equilibrium set of matches between student and colleges from which no student and university would prefer to change the match. Many markets such as marriage (Becker, 1973), labor (Abowd et al., 2004), and venture capital financing (Sørensen, 2007b) exhibit two-sidedness. Gale and Shapley (1962) show that the matching process in two-sided markets would create *sorting*. In particular when the production function exhibits complementarity of inputs (Becker, 1973; Kremer, 1993) the two-sided matching process would result in *positive* sorting of matches where agents with similar preferences, skills, traits, etc. are matched with each other. The complementarity of inputs in production would result in a unique and stable equilibrium where the equilibrium is characterized by assortative matching of inputs.

this two-sided selection bias is similar to the omitted variable bias ⁵. A methodological approach I use in this study is to estimate the potential omitted variables pertaining to unobserved worker and firm quality from a selection equation and include them in the outcome equation to effectively eliminate the two-sided selection bias. Below I describe this approach.

2.5.1 Individual and Firm Fixed Effects as Measures of Worker and Firm Quality

Since two-sided selection bias is equivalent to omitted variable bias finding proxy variables that capture worker and firm quality and including them in the outcome equation can mitigate the bias. Usually, there is no perfect measure of worker and firm quality in employer-employee linked datasets such as the one I use in this study. Hence

First I define a matching equation that best captures the effects of the match between the firm and employees. One such matching equation is the standard wage or income equation. A simplest way through which the matching between firm and employees manifests itself is through its effect on the wage of individuals (Topel, 1990; Abowd et al., 1999). In another words the wage of the individual can be used to proxy for the quality of the match between the firm and the worker (Jovanovic, 1979b; Topel and Ward, 1992a). To put this into context, consider the following wage equation,

$$w_{it} = x_{it}\beta_1 + z_{J(i,t)}\beta_2 + \theta_i + \psi_{J(i,t)} + \epsilon_{it} \quad (2.10)$$

in which w_{it} is the wage of individual $i = 1, \dots, N$ at time $t = 1, \dots, T$. x_{it} is the vector of all the time varying characteristics of individuals and $z_{J(i,t)}$ is the vector of the time varying characteristics of firms $j = 1, \dots, M$. θ_i is the pure individual effect and $\psi_{J(i,t)}$ is

⁵Heckman (1979) provided the first econometric treatment of endogeneity due to sample selection bias and showed that selection bias is equivalent to omitted variable bias. The omitted variable is the inverse Mills ratio that is calculated from a selection equation

the pure firm effect for the firm at which individual i is employed at time t . ϵ_{it} is the error term.

In matrix notation equation (2.10) is written as

$$W = X\beta_1 + Z\beta_2 + D\theta + F\psi + \epsilon \quad (2.11)$$

where X is a $N^* \times P$ matrix of time varying individual characteristics, Z is a $N^* \times Q$ matrix of time varying characteristics of the firm in which individual i works at time t , D is a $N^* \times N$ matrix of dummy variables for individual i , F is a $N^* \times M$ matrix of dummy variables for the firm in which individual i works at time t . W is a $N^* \times 1$ vector of annual individual wage, ϵ is a vector of residuals, and $N^* = NT$. The parameters of equation (2.11) are β_1 , $P \times 1$ vector of coefficients for the time varying individual characteristics; β_2 , $Q \times 1$ vector of coefficients for the time varying characteristics of the firm in which individual i works at time t ; θ , $N \times 1$ vector of individual effects; ψ , $M \times 1$ vector of firm effects.

Estimating equation (2.11) will give the estimates of the θ and ψ parameter vectors that correspond to the matrices of individual and firm fixed effects. In the next step, I use the estimates of the individual and firm fixed effects as proxies for worker and firm quality and include them in the second stage model to predict entrepreneurship. The second stage model is the outcome equation,

$$Y = X\beta_1 + Z\beta_2 + \theta\beta_3 + \psi\beta_4 + \epsilon \quad (2.12)$$

where Y is a dummy variable that takes a value of 1 if the employee spins off to start a new firm and 0 if the employee stays with her firm. θ and ψ are now vectors of individual and firm fixed effects respectively. The parameters β_3 and β_4 are the coefficients for the fixed individual and firm effects. X and Z are defined as before. Due to the non-linearity of the outcome equation, a link function can be used for appropriate estimation of the

equation (2.12),

$$P[Y_i = j] = \Lambda(X\beta_{1j} + Z\beta_{2j} + \theta\beta_{3j} + \psi\beta_{4j}) \quad (2.13)$$

where the link function Λ has a logistic distribution.

2.5.2 Estimation

Although equation (2.11) is just a classical linear regression model, its estimation becomes computationally cumbersome when the number of individual and firm indicator variables increases.⁶ Longitudinal employer-employee datasets typically have millions of individuals and thousands of firms. Including indicator variables for every individual and every firm in the regression equation creates a high dimensional design matrix, $[XZDF]$, that can't be inverted easily using the computational power of existing computers.⁷

Below I describe a practical way of estimating (2.10) when the design matrix is high dimensional. The approach is based on the recent developments in panel data models in estimating the *components of the error structure* (Abowd et al., 1999, 2002; Andrews et al., 2006; Woodcock, 2008).

Consider the following normal equations corresponding to equation (2.11),

$$\begin{bmatrix} X'X & X'Z & X'D & X'F \\ Z'X & Z'Z & Z'D & Z'F \\ D'X & D'Z & D'D & D'F \\ F'X & F'Z & F'D & F'F \end{bmatrix} \times \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\theta} \\ \hat{\psi} \end{bmatrix} = \begin{bmatrix} X'W \\ Z'W \\ D'W \\ F'W \end{bmatrix} \quad (2.14)$$

⁶Least Square Dummy Variable (LSDV) specification is a direct approach of estimating the fixed effects in an OLS regression.

⁷Standard OLS estimation of the equation (2.11) requires inverting a matrix with the columns size of $N + M + P$ and the row size of N^* . In the Swedish employer employee matched dataset both the column and rows of this design matrix exceeds millions. Inverting such a huge matrix requires tremendous amount of memory and computational power which exceeds current ability of computers and statistical packages.

as said earlier, simultaneously solving for the parameters of the above normal equations is not feasible given the high dimensionality of the design matrix. Therefore I proceed with the estimation in a series of steps using partial regression methodology (Greene, 1993). First I regress W and each columns of X and Z on the two sets of fixed effects $[D, F]$ and obtain the residuals. Second I regress the residual from the first regression, W on $[D, F]$, on the residuals obtained from regressing each columns of X and Z on $[D, F]$. This will give consistent estimates of β_1 and β_2 . I estimate these series of regressions using conjugate gradient algorithm with Abowd et al. (2002) grouping conditions.⁸ After obtaining $\hat{\beta}_1$ and $\hat{\beta}_2$ I recover the estimates of θ and ψ with the standard OLS formula,

$$\begin{bmatrix} D'D & D'F \\ F'D & F'F \end{bmatrix} \times \begin{bmatrix} \hat{\theta} \\ \hat{\psi} \end{bmatrix} = \begin{bmatrix} D' \\ F' \end{bmatrix} \times \begin{bmatrix} W - X\hat{\beta}_1 - Z\hat{\beta}_2 \end{bmatrix} \quad (2.15)$$

To solve the above systems of equations I use CGA algorithm. The CGA algorithm is described in appendix B.

2.6 Results

Descriptive statistics are shown in table 2.1. Earnings are defined as raw wages for paid employees and sum of raw wages and capital gains for firm owners.⁹ Average level of mobility in the economy is about 14% of which only about 3% of the moves is to start a new firm. The general rate of transition to entrepreneurship from paid work is about 0.5% in the Swedish economy. Table 2.2 reports correlations among dependent and independent variables. Propositions one and two stated that the likelihood of transi-

⁸It should be noted that estimation of these series of regressions are greatly simplified because the fixed effects matrices are diagonal and sparse, and because they are symmetric positive definite their Cholesky factorization exists and can be efficiently used to calculate the matrix product.

⁹In regression analysis I include dummy variable for ownership to distinguish paid employees from firm owners or any partnership status individuals.

tion to entrepreneurship from wage work increases with both individual quality and firm quality. As described in the methodology section I use estimates of individual and firm fixed effects from the wage regression to proxy for individual and firm quality. Next, I insert these estimates in a second regression to investigate their effect on entrepreneurial transitions. Column 2 of table 2.3 reports the result of this regression. The dependent variable in column 2 is a dummy variable that takes a value of 1 if the employee starts a new firm in the subsequent year and 0 if the employee stays with the current employer. Because of the nonlinearity of the regression equation I use logistic specification. Column 2 shows a full model with controls for a variety of observable individual and firm characteristics as well as a full set of dummy variables pertaining to geographic location of the employing firm, industry, and year of observations. The direction and significance of control variables are consistent with existing evidence about observable characteristics of individuals and entrepreneurship except for age. The coefficient of age is negative and statistically significant. The reason for the negative effect of age on entrepreneurship is because of its negative correlation with individual fixed effect. Therefore omitting individual fixed effects in the regression upwardly biases the effect of age. Consistent with proposition one and two, the coefficients of estimated individual and firm fixed effects are positive and statistically significant, $\hat{\beta}_{\hat{\theta}} = 0.6914$ ($p < 0.001$) and $\hat{\beta}_{\hat{\psi}} = 0.358$ ($p < 0.001$). Interestingly, the effect of individual quality is approximately twice as large as the effect of firm quality.

Proposition 4 stated that employees of high quality firms are less likely to switch firms. Empirically this implies that I should see lower probability of employee turnover among high quality firms compared to lower quality firms. Column 1 of table 5 tests for this proposition in a turnover regression. The dependent variable is a dummy that takes a value of 1 if the employee switches to another incumbent firm in the subsequent year and 0 if the employee stays with the current employer. As shown the effect of firm quality, measured by the estimated fixed effects, is negative and statistically significant, $\hat{\beta}_{\hat{\psi}} =$

-0.042 ($p < 0.001$). This implies that one standard deviation increase in firm quality reduces the odds of employee turnover by about 4%.

Now I turn to investigate the prediction in proposition 3. The comparative statistic leading to proposition 3 implies that the optimal cut off wage of the outside firm increases with its quality. This in turn implies that high quality workers switch to high quality firms upon mobility. Empirically I test this proposition at the time when individuals' switch firms. In particular I investigate whether the estimated individual fixed effect is positively correlated with the estimated fixed effect of the destination firm at the time when an employee switches firms. The correlation coefficient between individual fixed effect and the destination firm's fixed effect is 0.05 which is small but still positive indicating that in fact high quality individuals may sort into high quality firms upon mobility. When I break the correlations with firm size patterns slightly change. The correlation increases as the size of the destination firm becomes larger. For very large firms, with the number of employees greater than 1000, the correlation between individual and firm fixed effects become 0.1782. This observed pattern might be because large firms have better human resource practices that enable them to screen prospective workers better than small firms. Also on the individuals' side large firms might be more visible in the labor market therefore enabling individuals to associate quality rankings to them. This eventually makes best employees to make less error in selecting among larger firms. Next I formally investigate this relationship in an OLS regression framework using observations where employees switch firms between two consecutive periods. Table 2.4 shows the results of this analysis. The dependent variable is the destination firms' estimated fixed effects and the independent variable is the estimated individual fixed effect. I include a variety of individual characteristics as controls for the confounding effects of these variables with the quality of the destination firm. In addition I control for the destination firms' age, number of employees, and number of establishments which might be correlated with the choice of individuals to sort based on these characteristics at the

time of switching firms. I also include a full set of dummy variables pertaining to the year of observations, geographic location, and the industry of the destination firms. The results of the OLS regression shows a modest but statistically significant effect of the individual fixed effect on the destination firms' estimated fixed effect. The magnitude of the effect is 0.0174 implying that one standard deviation increase in the quality of the employee increases choosing a destination firm with a fixed effect (quality) of about 2% more upon mobility.

2.7 Robustness Checks

2.7.1 Alternative specification

Here I simultaneously estimate the effects of individual and firm fixed effects on mobility and entrepreneurship of employees. In this case the dependent variable consists of three alternatives: staying with the current employer, moving to another firm, and entrepreneurship. Given the individual level of analysis, the dependent variable can be interpreted as the outcome of individuals' choice between three alternatives, where the individual's attributes determines choice. This type of formulation of individual's decision making requires statistical models that are appropriate for microeconomic models of choice based on *utility maximization* which are subjected to constraints (Maddala, 1986). The most appropriate of models are the class of *Multiple choice models* based on utility maximization (McFadden, 1974; Boskin, 1974; Schmidt and Strauss, 1975b,a). Hence, in this study I formulate my structural model as multinomial logit.¹⁰ In ap-

¹⁰multiple choice models are often formulated as either *multinomial logit* or *conditional logit* depending on the *unit of analysis* of the structural model. For instance analyzing an individual's choice among several alternatives can be done by either multinomial logit or conditional logit. However, multinomial logit focuses on the individual as the unit of analysis and uses the individual's characteristics as explanatory variables in the structural model. In contrast the conditional logit model focuses on the alternatives and uses the characteristics of the alternatives as explanatory variables in the structural model. Although statistically the key difference between multinomial and conditional logit models involves the appropriate unit of analysis, the more important difference is rooted in behavioral assumptions about individual decision making (Hoffman and Duncan, 1988). I choose multinomial logit instead of conditional logit model is because of our assumption that individual attributes as well as changes in those attributes over time determines the attractiveness of the alternative choices in each time period.

pendix C I provide a formal elaboration on multiple choice models and multinomial logit specification.

The results of multinomial logit regression are shown in table 2.5. The base outcome is staying with the current employer in the subsequent year. The effects of individual and firm fixed effects on entrepreneurial transition remains positive and statistically significant. In addition the effect of firm fixed effect on mobility is negative and statistically significant. These results further confirm the predictions of the model.

2.7.2 Co-worker fixed effects as an alternative for firm fixed effect

Recent research suggest that the estimated firm fixed effect might be biased because of the non-monotonicity of wages that firms offer (Eeckhout and Kircher, 2011; De Melo, 2009) to allow for equilibrium mismatches to occur. Eeckhout and Kircher (2011) find that wages of a given worker have an inverted U shape. This reflects the opportunity cost of a firm to match with an inappropriate worker in equilibrium. In addition because of the lower mobility rates among small firms the estimated firm fixed effects for small firms might be biased which in turn may result in spurious correlation with individual fixed effects. Therefore since the estimated firm fixed effects might actually not conform to the exact quality of the firm, here I develop a novel measure to proxy for firm quality. This new measure of firm quality is the average of the individual fixed effects of a focal employee's coworkers at her destination firm. In other words,

$$\bar{\theta}_{i,t}^{co-workers} = \frac{\sum_{k \in J(i,t)} \theta_k}{N_{J(i,t)} - 1} \quad (2.16)$$

The correlation between individual fixed effect and the average fixed effect of the individual's co-workers at the destination firm is 0.3392 which is positive and considerably large in comparison with the correlation of the estimated individual and destination firm

fixed effects. This suggests that positive assortative matching exists where high quality employees match with firms that have high quality co-workers as well. In fact this is intuitive in the equilibrium of a labor market that exhibits positive assortative matching.

2.8 Conclusion

I started by identifying a void in the labor economics and entrepreneurship literature. Labor economics literature has made a significant contribution to the theories of turnover and employee mobility. However, these literature usually treat destination firms homogeneous. Individuals indeed may depart to existing incumbent firms or to form their own firm. Entrepreneurship literature on the other hand usually has its own theories about entrepreneurship by individuals. These two literature seldom speak to each other. In this research I attempted to bridge this gap and embed entrepreneurship into the mobility process. In particular I used a feature of the labor market, namely sorting, to build a theory about the mobility and entrepreneurship by employees of incumbent firms. Two interesting results emerge. First I show that labor market exhibits positive assortative matching when firm quality is measured by the quality of its employees. Second the results show that context matters a lot. Employees working at high quality firms are entering to entrepreneurship at a disproportionately larger rate.

Table 2.1: Descriptive Statistics

	mean	sd	min	max
Mobility	0.138	0.344	0.000	1.000
Entrepreneurship	0.005	0.069	0.000	1.000
Entrepreneurship Mobility	0.030	0.171	0.000	1.000
Age	39.495	10.750	20.000	59.000
Female	0.347	0.476	0.000	1.000
Swedish Background	0.868	0.338	0.000	1.000
Education <=11 Years	0.507	0.500	0.000	1.000
Education =12 Years	0.225	0.417	0.000	1.000
Education >12,<=15 Years	0.260	0.439	0.000	1.000
Education >15 Years	0.008	0.091	0.000	1.000
Earnings	260614.225	182165.095	0.000	43429240.000
Tenure	6.622	5.055	1.000	22.000
Firm Age	11.007	5.526	1.000	22.000
Employer's Nr. of Employees	2604.683	5881.483	20.000	42714.000
Nr. of Establishments >1	0.671	0.470	0.000	1.000
Standardized value of Individual Fixed Effect	0.032	0.979	-15.999	7.414
Standardized value of Firm Fixed Effect	-0.018	0.989	-11.140	6.522
Observations	17969079			

Table 2.2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Mobility	1.00																
(2) Entrepreneurship		1.00															
(3) Entrepreneurship Mobility			1.00														
(4) Age	-0.16	-0.01	0.05	1.00													
(5) Female	-0.00	-0.01	-0.03	-0.03	1.00												
(6) Swedish Background	-0.00	-0.00	-0.00	0.01	-0.03	1.00											
(7) Education <=11 Years	-0.09	-0.02	-0.00	0.24	-0.04	0.00	1.00										
(8) Education =12 Years	0.05	0.00	-0.02	-0.22	0.03	0.01	-0.55	1.00									
(9) Education >12,<=15 Years	0.05	0.02	0.02	-0.07	0.02	0.01	-0.60	-0.32	1.00								
(10) Education >15 Years	0.00	0.00	0.01	0.01	-0.02	-0.07	-0.09	-0.05	-0.05	1.00							
(11) Earnings	-0.02	-0.00	0.01	0.20	-0.22	0.05	-0.18	-0.05	0.24	0.08	1.00						
(12) Tenure	-0.19	-0.03	0.04	0.45	-0.05	0.06	0.22	-0.12	-0.13	-0.03	0.09	1.00					
(13) Firm Age	-0.01	0.00	0.01	0.03	-0.03	0.00	-0.04	0.02	0.03	0.00	0.10	0.19	1.00				
(14) Employer's Nr. of Employees	-0.06	-0.01	-0.01	0.06	0.06	-0.00	0.02	-0.01	-0.01	0.00	-0.03	0.01	-0.08	1.00			
(15) Nr. of Establishments >1	-0.04	-0.01	-0.01	0.06	0.04	0.01	-0.03	-0.01	0.04	0.00	0.02	0.06	0.04	0.29	1.00		
(16) Individual Fixed Effect	0.09	-0.02	-0.01	0.34	-0.34	0.11	0.50	-0.37	-0.19	-0.11	0.40	0.23	-0.02	-0.02	-0.01	1.00	
(17) Firm Fixed Effect	-0.05	0.00	-0.02	-0.01	-0.04	-0.02	-0.01	-0.02	0.03	0.01	0.06	-0.09	-0.69	-0.11	-0.11	-0.01	1.00
Observations	21209779																

Table 2.3: Logit Regression of Employee Mobility and Entrepreneurship

	(1)	(2)
	Mobility	Entrepreneurship
Individual Fixed Effect	0.290*** (0.00100)	0.691*** (0.0124)
Firm Fixed Effect	-0.0424*** (0.00154)	0.358*** (0.0183)
Female	-0.144*** (0.00181)	-0.574*** (0.0278)
Swedish Background	0.0795*** (0.00225)	0.190*** (0.0330)
Age	-0.0243*** (0.0000843)	-0.00872*** (0.00109)
Tenure	-0.0973*** (0.000218)	-0.0410*** (0.00226)
Education ≤11 Years	0.00466* (0.00221)	-0.863*** (0.0299)
Education >12, ≤15 Years	0.0578*** (0.00208)	0.238*** (0.0272)
Education >15 Years	-0.0785*** (0.00821)	0.945*** (0.0842)
Firm Age	0.0393*** (0.000273)	0.0566*** (0.00324)
Log Nr. of Employees	-0.0807*** (0.000561)	-0.205*** (0.00737)
Nr. of Establishments >1	0.0358*** (0.00200)	0.189*** (0.0245)
Constant	2.521*** (0.0258)	-3.699*** (0.209)
Observations	17969064	15506761
Pseudo R^2	0.151	0.203
Log Likelihood	-6107138.8	-82595.3
χ^2	2177609.5	41949.5
P-value	0	0

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.4: OLS Regression of Labor Market Sorting

	DV: Destination Firm's Fixed Effect
Individual Fixed Effect	0.0174*** (0.000611)
Female	-0.0543*** (0.00104)
Swedish Background	0.0484*** (0.00130)
Age	-0.000389*** (0.0000476)
Education <=11 Years	-0.0575*** (0.00131)
Education >12,<=15 Years	0.132*** (0.00120)
Education >15 Years	0.107*** (0.00471)
Destination Firm's Age	-0.149*** (0.0000758)
Destination Firm's Log Nr. of Employees	0.0121*** (0.001263)
Destination Firm's Nr. of Establishments >1	-0.0235*** (0.000995)
Constant	1.569*** (0.0109)
Observations	1644135
R^2	0.762

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies for the destination firm.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5: Multinomial Logit Regression of Employee Entrepreneurship.

Base Outcome: Staying with the Current Employer		
	Mobility to an Established Firm	Entrepreneurship
Individual Fixed Effect	1.356*** (0.00212)	1.965*** (0.0228)
Firm Fixed Effect	0.967*** (0.000988)	1.438*** (0.0239)
Female	0.881*** (0.00162)	0.545*** (0.0141)
Swedish Background	1.083*** (0.00247)	1.224*** (0.0376)
Age	0.975*** (0.0000834)	0.989*** (0.00102)
Tenure	0.906*** (0.000201)	0.956*** (0.00197)
Education ≤ 11 Years	0.997 (0.00223)	0.432*** (0.0121)
Education $>12, \leq 15$ Years	1.049*** (0.00221)	1.289*** (0.0326)
Education >15 Years	0.917*** (0.00766)	2.520*** (0.202)
Firm Age	1.042*** (0.000290)	1.058*** (0.00312)
Log Number of Employees	0.925*** (0.000526)	0.795*** (0.00548)
Nr. of Establishments >1	1.037*** (0.00211)	1.215*** (0.0278)
<i>N</i>	17907289	
pseudo R^2	0.152	
Base Outcome	0	
Log Likelihood	-6067831.5	
χ^2	2169243.5	
P-value	0	

Exponentiated coefficients; Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3 Essay Two: Matching and Transition to Entrepreneurship

3.1 Introduction

Employees often leave their employers (spinoff) to start their own firm. These entrepreneurs emerging from existing firms are thought of as distinctive class of entrepreneurs. They contribute to the evolution of nascent industries such as semiconductors (Klepper, 2009a), automobiles (Klepper, 2007), and disk drives (Christensen, 1993)¹¹. In addition, spinoffs formed by ex-employees of incumbent firms contribute to the emergence of industry clusters (Buenstorf and Klepper, 2009) and serve as a conduit for knowledge spillovers (Agarwal et al., 2007). Although considerable progress has been made about the causes and consequences of entrepreneurial departure of employees (Phillips, 2002; Agarwal et al., 2004; Klepper and Sleeper, 2005; Franco and Filson, 2006; Sørensen, 2007a; Carnahan et al., 2012)¹², except for a few recent studies (Elfenbein et al., 2010; Astebro et al., 2012; Campbell et al. 2012; Ganco, 2013) there is still little known about when employees leave wage work to start their own firm and which employees are more likely to do so? Since transition from wage work to entrepreneurship constitutes a labor market outcome for the individual, the relationship is best understood if entrepreneurship could be embedded into the mobility process of individuals (Sørensen and Fassiotto, 2011; Sørensen and Sharkey, 2010). In this paper I employ this perspective and investigate the relationship between labor market matching and transition to entrepreneurship from wage work. Matching in the labor market (Viscusi, 1979; Jovanovic, 1979b) is a canonical model of turnover in micro-economics of labor markets and it has also been embedded in the macro-economic search models (Moscarini, 2005). Thus matching is a

¹¹Evolution of nascent industries is tightly linked to spinoff entry. For instance in early semiconductor industry, Fairchild Semiconductors spawned more than 20 firms salient examples of which are Intel, Advanced Micro Devices, and National Semiconductor. Throughout the evolution of the semiconductor industry from 1957 to 1986 nearly 100 firms entered the industry, almost all of which were spinoffs(Klepper, 2009a).

¹²Most of these studies take the firm as the level of analysis, leaving little opportunity for theorizing about the individual determinants of entrepreneurship.

natural starting to point to understand the occupational choice of individuals including their self-employment/entrepreneurship outcomes.

In this study I use Swedish employer-employee matched dataset and employ a novel empirical methodology to estimate the exact quality of the match between the employee and the employer. The empirical methodology decomposes productivity into individual, firm, and match specific components and uses the estimates of these fixed productivity components in a second stage mobility and entrepreneurship regressions. Similar decomposition of these fixed effects has recently been used to analyze sorting in the labor market (Abowd et al., 1999; Woodcock, 2008) and achievement and mobility of teachers between schools (Jackson, 2013). The results show a substantial effect of match quality on the labor market outcome of employees. Similar to past literature match quality is negatively related to turnover, however, match quality has a substantial effect on the entrepreneurial transition of employees as well. Both mismatched and well matched employees are likely to transition to entrepreneurship relative to moderately match employees. In addition, the type of entrepreneurial transition differs by match quality. High match quality is negatively related to transition from paid employment to self-employment¹³ whereas it is positively related to transition to incorporated spinoffs. This result points to the argument that both mismatched employees and well matched employees transition to entrepreneurship from wage work, albeit founding different types of entrepreneurial entities. Furthermore quality of the match is positively related to team entrepreneurship and starting a business in the same industry as the prior employer. I combine Lazear's (2005) intuition of balanced skills and entrepreneurship with Lazear's (2009) model of job matching and create a simple model that explains these results.

¹³Throughout the paper I define self-employment as founding sole-proprietorship entities.

3.2 Matching, Skill Acquisition, and Entrepreneurship

3.2.1 General and Firm Specific Human Capital

Becker (1962) made a distinction between two types of human capital: general human capital which helps productivity not only at the current firm but also at other firms, and firm specific human capital which increase productivity only at the firm where the individual works. General human capital consists of skills and abilities that are acquired by individuals through formal education or on-the-job training (Becker, 1962; Rosen, 1981). It is usually thought that investment in general human capital is associated with less productivity loss because those skills are not transaction specific (Williamson, 1979) and could be easily transferred to other firms. Firm specific human capital, on the other hand, is comprised of skills and abilities that are only acquired on-the-job in a particular employer (Parsons, 1972; Jovanovic, 1979a). By definition these skills are transaction specific (Williamson, 1979; Carmichael, 1983) and their value is lost when individuals switch employers. A follow on question to ask is when individuals invest in general versus firm specific human capital? As said, investment in firm specific human capital comes with a tradeoff. Firm specific human capital increases the productivity of workers more than general human capital (Topel, 1990) however at the expense of limiting their mobility options to other firms (Coff, 1999). From the firms perspective firm specific human capital is more valuable than general human capital as well. This is probably salient in strategic management research where a firms performance and competitive advantage hinges on its idiosyncratic and non-transferable resources (Penrose, 1959; Barney, 1991; Grant, 1996). In fact, firm specific human capital is more valuable and most inimitable and could lead to superior performance when it is used in the firm where it was originally developed (Hitt et al., 2001; Hatch and Dyer, 2004). For individuals this tradeoff is important because an alternative way for them to increase their wages is to switch firms to find a better matching firm (Jovanovic, 1979b; Topel and Ward, 1992b) . Therefore the quality of the match between the individual and the firm directly

affects the investment in skills. To illustrate the investment in types of skills I employ the skill weights approach originally developed by (Lazear, 2009).

Lazear (2009) argues that firm specific human capital is actually general human capital which is weighted differently in different firms. In other words firms use a variety of skills which are general in nature meaning that they are also used in other firms. The difference however is that firms vary in weighting of different skills. Since productivity associated with firm specific human capital is more than that of general human capital investment in firm specific human capital is always preferred as long as the quality of the match is sufficiently high.

Workers whose match quality is sufficiently high will have higher incentives to invest in specific human capital than workers whose match quality is revealed to be poor. This is because workers with high match quality expect to continue the employment relationship for a long period of time compared to workers whose match quality is poor. As Lazear (2009) shows workers whose match quality is low (or their expectation about match quality is low) invest in general skills, which is valuable in other firms as well, and conversely workers whose match quality is high specialize in the skill set that is specific to their current employer.

3.2.2 Model

I assume that individuals are endowed with two skills: s_t^A and s_t^B with $s_t^A, s_t^B \geq 0$. The subscript t denotes time. Thus at time 0 the skill mix of an individual is denoted by the vector (s_0^A, s_0^B) . I further assume that individuals are heterogeneous with respect to their skill mix and as in Roy (1951) they might have comparative advantage in one skill than the other. Given this initial skill mix the individuals output in paid work is,

$$S = \lambda_i s_0^A + (1 - \lambda_i) s_0^B \tag{3.1}$$

where $0 \leq \lambda_i \leq 1$. The parameter λ_i denotes the idiosyncratic weight that firm i places on the skill mix of the individual. Differentiating (1) with respect to parameter λ_i we get,

$$\frac{\partial S}{\partial \lambda_i} = s_0^A - s_0^B \quad (3.2)$$

The sign of equation (2) depends on the sign of $s_0^A - s_0^B$. In other words an individual that has a comparative advantage in s_0^A will have a larger output in firms with high λ_i . In this setting a mismatched individual is the one who has a comparative advantage in skill s_0^B but he is matched with a firm with high λ_i . As in Lazear (2009), the parameter λ_i can be thought of the match quality between the skill requirements of the firm and the skill mix of the individuals. For a worker with comparative advantage in s_0^A matching implies finding a firm with $\lambda > \lambda_i$.

Given the above setting I now proceed to the timing of the events. At time 0 individuals are randomly matched with firms. In other words the quality of the match λ_i is initially unknown. During the period one the worker discovers the quality of his match and invests in skills that add to his skill mix. I assume that the degree of specialization in period one is directly related to the quality of the match: workers who are well matched with their firm invest more in the skill that they have comparative advantage in, and those who are mismatched will invest more on the skill in which he has comparative disadvantage.

To induce entrepreneurship in the model I assume that at time 2 entrepreneurial opportunities arrive. Following Lazear (2005) I assume that entrepreneurship requires balanced skill set. In other words in an entrepreneurial firm the worker performs both tasks himself whereas in the paid work he only needs to be skilled in one of them. This notion is also used in Åstebro et al. (2011) albeit in the different model. The entrepreneurial payoff for the individual who has comparative advantage in skill A and

match quality λ_i is given by,

$$y = \lambda_i(s_1^A + s_1^B) - C(\lambda_i, s_1^B) \quad (3.3)$$

where

$$C(\lambda_i, s_1^B) = [(2\lambda_i - 1)s_1^B]^2 \quad (3.4)$$

The first term in the entrepreneur payoff function characterizes the entrepreneurial output. The entrepreneur can use both skills in production in equal weights. The maximum weight that he can carry over from her prior employer is constrained by her match quality, the parameter λ_i . Since match quality determines the degree of specialization in one or the other skill it captures the idea of the transfer or inheritance of knowledge from an existing firm to an entrepreneurial firm (Klepper and Sleeper, 2005; Franco and Filson, 2006). Balancing skills in the entrepreneurial firm however comes with a cost. The second term in equation (3) captures the cost of balancing the weakest skill. The cost function is characterized by a quadratic loss function as in Jovanovic and Nyarko (1996) and Ohyama (2013). The cost function is basically the adjustment cost necessary to balance the skills and the quadratic nature of it makes it extremely costly to balance the skills when the difference between the two skills is high. To analyze the entrepreneurial decision we only need to compare the payoffs from entrepreneurship with the payoffs from wage work at the end of period 1,

$$\lambda_i(s_1^A + s_1^B) - C(\lambda_i, s_1^B) \geq \lambda_i s_1^A + (1 - \lambda_i)s_1^B \quad (3.5)$$

The individual departs paid work for entrepreneurship if (3.5) holds. Rearranging the terms leaves the following earnings function that the entrepreneur wants to maximize,

$$g(\lambda) = (2\lambda - 1)s_1^B[1 - (2\lambda - 1)s_1^B] \quad (3.6)$$

For convenience I suppress the subscript of λ . The above earnings function captures

Lazear's (2005) intuition that the payoff to entrepreneurship is determined by the skill in which the worker has the lowest ability. However it should be noted that we depart from Lazear (2005) by allowing the entrepreneur to acquire the skill in which he is less capable of at a cost given in (3.4) which is convex in investment. The entrepreneur's decision is to maximize (3.6). The solution to this maximization problem is two cut-off points: λ_L and λ_H where $0 < \lambda_L < \lambda_H < 1$. Individuals depart to entrepreneurship when their match quality is above the cut-off λ_H and below the cut-off λ_L . Individuals whose match quality is above λ_H are workers who have high ability in one of the skill dimensions and lack ability in the other skill dimension. These individuals will get greater entrepreneurial payoff from balancing their skill set where the entrepreneurial payoff outweighs the costs of balancing the skill set. Similarly individuals whose match quality is below λ_L are workers who are mismatched with their firm on the required skill dimensions and therefore invest in general skills during the period one. In other words, since they are mismatched they will balance their skills on the job. They will depart to entrepreneurship because they incur lower costs for adjusting their skill mix. These cut-off points are shown in figure 1.

< INSERT FIGURE 1 HERE >

The above model predicts a U-shape relationship between match quality and entrepreneurship that is captured in the following proposition,

Hypothesis 1: *workers with match quality $\lambda_i \geq \lambda_H$ or $\lambda_i \leq \lambda_L$ become entrepreneurs at the end of period 1. Workers with match quality $\lambda_L < \lambda_i < \lambda_H$ remain wage workers.*

3.2.3 Quality of Spinoff Firms

The direct corollary of hypothesis 1 is to compare the characteristics of the entrepreneurial firms given the founders' match quality with their prior employers.

Assuming that the quality of a startup firm depends on the founder's human capital, the model gives predictions about the type of entrepreneurial firms founded with respect to match quality. Since entrepreneurs can incur a cost to balance their skills the quality of the entrepreneurial firm is determined with their highest skill in wage work. In other words at the end of period 1 the highest skill that the individual transfers to the startup is denoted by $\max(s_1^A, s_1^B)$. As in Lazear (2009) investment in skills on the job depends on the quality of the employer-employee match. In wage work, individuals with high match quality specialize in one skill whereas individuals with low match quality become generalists. Thus the highest skill that entrepreneurs transfer to the startup firm at the time of transition increases with match quality. Entrepreneurs who specialize on the job are likely to found growth oriented firms in which they use their specific knowledge. On the contrary entrepreneurs who become generalists on the job are likely to have a lower depth of skills necessary to found growth oriented firms. Therefore I hypothesize:

Hypothesis 2: *The likelihood of founding growth oriented businesses increases with match quality.*

The second comparison is with respect to the cost of balancing the skill mix. Entrepreneurs with high match quality are constrained with respect to their skill mix whereas mismatched entrepreneurs are unconstrained. This is because the first order condition of the cost function, equation (3.4), is increasing in the quality of the match, λ_i . In other words high match quality entrepreneurs have more unbalanced skill mix and incur a substantial cost to balance their skill mix when entrepreneurial opportunities arise. On the contrary mismatched entrepreneurs invest in both skills during wage work and incur lower cost of balancing skills when entrepreneurial opportunities arise. This difference in the cost of balancing the skill mix has implications for team entrepreneurship. Contrary to Lazear (2005) that argues that the entrepreneur must invest in her worst skill to increase business performance, one way to balance the skill

mix is to team up with other employees who have comparative advantage in other skills. Åstebro and Serrano (2011) in studying business partnerships among Canadian inventors find that nearly 65% of the business partnerships are formed to obtain complementary human capital. Teaming up with other employees allows the entrepreneur to benefit from the complementary skill set of other employees (Ganco, 2013).

As the quality of the match between an employee and a firm increases so does the quality of her match with other co-workers (Muendler and Rauch, 2012; Eisenhardt and Schoonhoven, 1990).

I therefore formulate the following hypothesis:

Hypothesis 3: *Among entrepreneurs, the likelihood of spinoff with a team increases with match quality.*

Furthermore the model illustrates that the two groups of entrepreneurs differ in their human capital composition at wage work given the quality of the match. The difference in the human capital composition of workers can inform us about the industry characteristic of their spinoff firms. Literature on employee entrepreneurship makes a distinction between intra-industry spinoffs and inter-industry spinoffs (Klepper, 2009b; Klepper and Thompson, 2010). Intra-industry spinoffs are entrepreneurial firms founded by ex-employees of incumbent firms in the *same* industry as that of the parent firm whereas inter-industry spinoffs are firms founded by ex-employees of incumbent firms in a *different* industry than that of the parent firm. This distinction is important because it is directly related to the nature of the human capital that founders transfer from their parent firms. As said, human capital is often accumulated on-the-job through learning by doing (Nagypál, 2007). Human capital is not only firm specific but it is also industry specific (Neal, 1995; Parent, 1999). Often times both firm specific and industry specific human capital are developed alongside each other within an individual's tenure in the firm. Thus the human capital composition of well matched employees is not

only comprised of firm specific components but it is also comprised of industry specific components. On the contrary since mismatched employees invest in general human capital, it is likely that their industry related human capital remain general well.

Prior research suggests that cross industry relatedness of skills is one of the determinants of inter-industry mobility Neffke and Henning (2013). Thus if match quality is related to the composition of human capital that individuals acquire on the job I shall at least observe a systematic relation between match quality and the industry related mobility. In particular entrepreneurial transitions within the same industry as the prior employer (intra-industry spinoffs) should increase with quality of the match. Therefore in a comparison group consisting of all the entrepreneurial transitions from wage work I posit that the following hypothesis should hold.

Hypothesis 4: *Among entrepreneurs, the likelihood of intra-industry spinoff increases with match quality.*

3.3 Related Models

The model presented above falls in the recent class of models predicting a bimodal selection to entrepreneurship. I will review these models here and explain their differences from the model I presented here. Åstebro et al. (2011) develop a model based on Kremer (1993) O-ring theory of production assuming that entrepreneurs are jack-of-all-trades based Lazear (2005). The key feature of their model is that convexity in earnings is achieved naturally because of the complementarity between tasks. In their model under the assumption of frictionless labor market there would be no entrepreneurship because earnings in wage employment dominate earnings in self employment. However, when imperfections exist in the labor market mismatches between employers and employees occur. The severity of mismatch on individual earnings will be higher at the tails of the ability distribution. The key take out of their model is that mismatched employees are more likely to select into entrepreneurship where both high and low ability indi-

viduals are more likely to choose entrepreneurship as an occupational choice than wage work. The key difference between the model I presented here and Åstebro et al. (2011) is that bimodality in selection to entrepreneurship is with respect to ability whereas in my model bimodality is with respect to match quality keeping ability constant. Another model by Poschke (2013) also generates a bimodal selection into entrepreneurship with ability. Poschke's model however is a search model where an agent searches for a project with ex-ante unknown productivity to work with. Selection into entrepreneurship arises as a result of the opportunity cost of forgone wages by searching for the entrepreneurial project. Low ability individuals have a low wage in paid work and therefore face a low opportunity cost of entry into entrepreneurship given that they encounter a reasonably good project. On the other hand high ability individuals have higher opportunity cost but also have higher potential benefits in entrepreneurship thereby may find it valuable to search of an entrepreneurial project to work with.

The closest model to the one I presented here is found in Ohyama (2013). Ohyama models entrepreneurship and wage work as a selection problem of adapting different grades of technology with different adoption costs. In his model individuals are assumed to have different job related human capital which determines their switching cost to work with a different grade of technology in entrepreneurship. Ohyama's model predicts a bimodal entry into entrepreneurship where individuals with high and low levels of job related human capital transition to entrepreneurship whereas individuals with moderate level of job related human capital remain wage workers. The key parameter of Ohyama's model is match between one's education and job which determines which grades of technology to adapt in entrepreneurship. The matching concept in the I presented here is more general in nature and allows for multiple occupational choices based on skill acquisition.

3.4 Data

Data for the empirical analysis comes from two matched longitudinal data sources from Sweden. The first is the longitudinal integrated database for medical insurance and labor studies (LISA) and the second is the firm financial statistics database (Företagens ekonomi (FEK)). Both databases are maintained by Statistics Sweden. LISA is a database of all the population of Swedish individuals maintained by Statistics Sweden (SCB). The LISA database is constructed by pooling multiple governmental registers: register based labour market statistics (RAMS), register of education, register of immigrants (SFI), total population register (RTB), income and tax register (LOT), population and housing census, and the business survey. The primary focus of the LISA database is individual, but it also links individuals to family, businesses and workplaces. Although the primary focus of the LISA database is the individual but it is the individual object that defines the population and various individual information can be aggregated to obtain data at the level of the population. The LISA database currently contains vintages from 1990 to 2009 and includes all the individuals whose age is 16 and older and who were registered in Sweden as of December 31st of each year. The longitudinal nature of LISA enables data for a single person to be linked together for all years that the person is registered in Sweden.

FEK is a firm financial information database which is based on the survey of all the business in Sweden for tax purposes. FEK is conducted annually and the complete information for all business is available from 1997 onwards. Firms in FEK are identified with a unique identification number which makes it possible to link FEK with other database such as LISA. Such integration will let individuals to be matched with firms and the individual information to be connected with the firm level information. The Swedish employer-employee matched data has recently been used by management scholars to study entrepreneurship (Giannetti and Simonov, 2009; Folta et al., 2010; Delmar et al., 2011), productivity effects of mergers, acquisitions, and corporate restructuring (Siegel

et al., 2009; Siegel and Simons, 2010).

3.4.1 Sample Construction

The extract of the LISA database available to me starts in 1986 and ends in 2008. For the analysis I use the panels from 1996 to 2007. The reason to start the panel in 1996 was arbitrary; however, I did not choose to have a longer panel simply because the larger number of observations would only add to the computational complexity that was beyond the capacity of my computer. Several measures however were calculated based on the information on prior panels such as the number of past jobs or tenure in 1996. I chose to end the panel in 2007 in order to observe the mobility of the individuals at the end of the panel. To do this I utilize the information from the 2008 extract of LISA. In addition I limit the analysis to individuals whose age is between 20 and 60 during the sample period to avoid non-random attrition due to retirement. This leaves me with 3,820,049 individual-year observations.

3.4.2 Key Variables

Several variables serve as dependent variables in this study. Two key dummy variables denote employment transitions in the data: mobility and entrepreneurship (spinoff). Mobility is defined when an employee switches employers in a subsequent year. I define entrepreneurship as an instance when an employee departs her current employer and founds a new firm. Statistics Sweden distinguishes entrepreneurs with sole proprietorship from those founding incorporated business¹⁴. According to the Swedish law an incorporated company requires a minimum share capital of roughly 8,000 USD. We use this information to test the predictions pertaining to the relation between match quality and the quality of the spinoff firms.

The main independent variable in this study is *match quality*. In the methodology

¹⁴See Henrekson and Sanandaji (2013) for an extensive discussion on self-employment and Schumpeterian entrepreneurship

section I describe the match fixed effects methodology that enables me to estimate the quality of the employer-employee match.

The main control variables in this study pertain to individual characteristics and time varying firm characteristics. All sources of variation related to geographic regions, industry, and year trends are included as fixed effects.

Wage. Individuals earning different levels of income might value the three alternative occupations differently. For instance, low income employees might value the option of switching to another employer more than high income individuals particularly because the opportunity cost of foregoing current wages to start a business or to switch to another employer is lower for low income employees. On the other hand high income employees might value the option of starting their own business more than the other alternatives since high income might also imply high wealth for business creation. We include the quadratic term of employee's wage as an additional explanatory variable in the model to capture the potential non-linear effect of wage on the choices. Indeed Campbell et al. (2011) shows that wage has a non-linear effect (inverted U shape) on the likelihood of entrepreneurship conditional on the mobility of employees.

Tenure. The variable "tenure" captures the cumulative employment duration of employees at the parent firm in each year. Theoretical and empirical works in labor economics (Jovanovic, 1979; Topel and Ward, 1992) show that turnover is decreasing with the tenure of workers.

Age. Another highly related variable to turnover and entrepreneurship is age. Age is consistently shown to be negatively related to worker turnover (Viscusi, 1980; Stumpf and Dawley, 1981). Regarding entrepreneurship the percentage of self employed individuals rises with age until around 45 and then remains constant until 60 and rises again sharply (Evans and Leighton, 1989).

Gender. Job quit rate as well as the rate of entrepreneurship are shown to be different among male and females. In general females exhibit more job quit rates than their male

counterparts (Viscusi, 1980; Loprest, 1992) and are less likely to become entrepreneurs than men (Blanchflower and Oswald, 1998). The job quit pattern of females and males might be related to the type of jobs that they chose to work (Viscusi, 1980). Therefore we control for the possible correlation of gender differences and the type of firms that they chose to work.

Education. Educational attainment of individuals is likely to be correlated with the type of job and company that they work. Educational attainment is therefore a means of selection in the labour market (Spence, 1973) for employers. Education is also shown to be related to turnover and mobility of workers Buchinsky et al. (2010)¹⁵.

I also control for the number of past jobs that individuals have held during their career and their citizenship status. In addition I control for a number of time varying firm attributes: average wage of the employer, the employer's number of employees (proxy for firm size), maximum attainable wage at the current employer that captures the extent that employees can advance during their tenure , and the age of the employer.

3.5 Methodology

3.5.1 Empirical Definition of Fixed Effects

The individual, firm, and individual-firm match effects are distinct concepts. Empirically these are usually called the fixed effects or heterogeneity (Greene, 1993)¹⁶. Individual effect is a factor that is specific to an individual and affects his outcome at all firms equally (e.g. innate ability or risk preferences). Similarly firm effect is a factor specific to each firm that affects the outcome of all individuals in a firm equally. Such factors can be idiosyncratic resources, brand, reputation, and knowledge assets. Match effects are fac-

¹⁵In rare instances educational level of individuals vary with the duration of their employment in a particular employment spell. Since educational level is a time invariant characteristic of individuals in their employment spell I recode educational level within an employment spell as the maximum of the observed educational level in that spell.

¹⁶The heterogeneity may be observed in the data such as race, sex, location, etc. or unobserved such as innate individual ability or preferences etc. all of which are assumed to constant over time. To the extent that the regression model includes observable time invariant components, the fixed effects capture the unobserved heterogeneity.

tors that are particular to each individual-firm pairing and are not portable across firms or individuals. They are the combination of characteristics that vary at the individual-firm pairing. For example certain individuals might be more productive in certain firms because of a fit with certain firm culture or coworkers. In other words match effect arises because of the systematic complementarities between a particular individual and a particular firm. These complementarities will be lost when individuals abandon their existing match and form a new match. In the empirical settings the fixed individual and firm effects are usually characterized by dummy variables for each individual and firm. As a result the match effect is captured by the interaction of individual and firm dummies.

3.5.2 Identification of the Fixed Effects

How to identify separately the individual, firm, and the match (individual-by-firm) effects? Individual effects on productivity are portable between employers which are identified based on the conditional covariation of individual productivity at different employers. Firm specific effects of individual productivity are the common component of productivity among all individuals employed in the same firm. Match effect is the component of individual productivity that is specific to each individual-firm pairing and is not explained by the individual and firm specific effects. Thus a key mechanism for separately identifying the individual, firm, and match effect is the mobility of individuals between firms. With the employer-employee matched datasets one can disentangle and estimate the individual, firm and match effects. To illustrate how identification is achieved consider the ideal empirical setting where all individuals are observed in all firms. In other words all individuals worked for a particular firm at some point in time and all firms employed a particular individual at some point in time. In this setting, assuming that matches are formed at random (e.g. there is no correlation between match effects and other regressors including individual and firm specific effects) the mean match

quality for each individual and each firm would be zero. Therefore conditional on all the other covariates, mean of the residuals for an individual i at firm j would be a consistent estimate of the individual-firm match. Subsequently the mean of the matches for individual i across all the firms would be consistent estimate of the individual specific effects, and the mean of the matches for firm j across all the individuals would be consistent estimate of firm specific effects. Therefore identification is achieved when many individuals are observed in a same set of firms.

To investigate the effect of match quality on employee mobility and entrepreneurship I follow a two step procedure where in the first step I estimate the individual, firm, and match effects from a *matching equation* and in the second step I estimate a *mobility regression* including the estimated fixed effects of the individual, firm, and the individual-firm match from the first step.

3.5.3 Matching Equation

Since the quality of the match is unobserved in the data I first need to infer it. To achieve this I create a matching equation as below. This matching equation is essentially a classic earnings regression.

$$\ln(w_{ijt}) = x_{i(j)t}\beta + \theta_i + \psi_j + \phi_{ij} + e_{ijt} \quad (3.7)$$

where w_{ijt} is the wage of individual i working in firm j at time t . $x_{i(j)t}$ is the vector of all the time varying characteristics of the individual and the time varying characteristics of the firm in which individual i works at time t . θ_i is the vector of individual fixed effects, ψ_j is the vector of firm fixed effects, and ϕ_{ij} is the vector of match fixed effects. Error structure is denoted by e_{ijt} . Abowd et al. (1999) use a similar structural model to decompose the productivity of workers into individual and firm specific effects. Woodcock (2008) augments the individual productivity regression by incorporating a match fixed

effect similar to the one that I use here. Since my interest lies in estimating the unobserved quality of the match between individuals and firms, ϕ_{ij} , I briefly elaborate on its meaning.

As said incorporating a match fixed effect in a regression equation is essentially equivalent to interaction of individual and firm dummies. The match fixed effect therefore captures a stable characteristic of the match between an individual and a firm that affect the wage of the individual. A low value of the match fixed effect denotes a poor match whereas a large value of the match fixed effect denotes a good match.

3.5.4 Estimation of the Matching Equation

As noted earlier the matching equation is comprised of three sets of fixed effects corresponding to individual, firm, and the individual-firm pairing. If one is not interested to estimate these sets of fixed effects a standard fixed effects methodology that restates the matching equation in terms of its deviation from individual-firm match means will sweep away all the fixed effects and will give consistent estimates of the β coefficient. However since we are interested to estimate the actual estimate of the fixed effects an alternative procedure is to use least square dummy variable approach (LSDV) (Abowd et al., 1999). LSDV introduces a full set of dummy variables for the individual, firm and their interaction which captures the match effects. Although LSDV is just a classical linear regression model its estimation becomes computationally cumbersome when inclusion of individual, firm, and match dummies creates a high dimensional design matrix that could not be inverted using conventional softwares and computational power of current computers (Abowd et al., 1999; Woodcock, 2008)¹⁷.

Longitudinal employer-employee matched datasets typically have millions of individual and hundred thousands of firms that prevents using the classic LSDV approach. Below I outline an alternative *orthogonal match fixed effects methodology* (Woodcock,

¹⁷The corresponding design matrix of equation (3.7) is $[X D F M]$ where D , F , and M are the matrices of individual, firm, and match indicators.

2008; Jackson, 2013) to estimate the fixed parameters. For convenience let's state equation (3.7) in matrix form. Denote N^* as total number of observations, N as total number of individuals, and J as total number of firms. Also denote M as total number of individual-firm matches, $M \leq NJ$. There are k number of time varying individual and firm covariates. Then,

$$W = X\beta + D\theta + F\psi + M\phi + \epsilon \quad (3.8)$$

where W is $N^* \times 1$ vector of log annual wage. X is a $N^* \times k$ matrix of time varying covariates which include both individual and firm characteristics, D is a $N^* \times N$ matrix of individual indicator variables, F is a $N^* \times J$ matrix of firm indicator variables, and M is a $N^* \times M$ matrix of indicator variables for each individual-firm match. β is a $k \times 1$, θ is a $N \times 1$, ψ is a $J \times 1$, and ϕ is a $M \times 1$ vector of parameters. ϵ is a $N^* \times 1$ error vector. The orthogonal fixed effects estimation proceeds as below. First using within match estimator (Greene, 1993) I estimate $\hat{\beta}$. This is easily achieved by first stating (3.8) in terms of deviations from individual-firm match means, which sweeps away the design matrix $[D F M]$, and then using OLS to obtain $\hat{\beta}$ ¹⁸. In the second step I use the well known property of partial regression methodology commonly known as Frisch-Waugh-Lovell theorem (Greene, 1993) and solve,

$$\begin{bmatrix} D'D & D'F \\ F'D & F'F \end{bmatrix} \times \begin{bmatrix} \hat{\theta} \\ \hat{\psi} \end{bmatrix} = \begin{bmatrix} D' \\ F' \end{bmatrix} \times [W - X\hat{\beta}] \quad (3.9)$$

where $[W - X\hat{\beta}]$ is the vector of least square residuals. Estimation of equation (3.9) renders $\hat{\theta}$ and $\hat{\psi}$. This estimation is computationally cumbersome because the dimension of the design matrix on the left hand side of (3.9) is still extremely large. In the appendix I describe an estimation procedure called conjugate gradient algorithm that gives the

¹⁸In mathematical terms $\hat{\beta}$ is obtained by: $\hat{\beta} = (X'G_{[DFM]}X)^{-1}X'G_{[DFM]}W$, where $G_{[DFM]}$ takes deviations from means within each match.

exact OLS solution for (3.9) without the need to invert a high dimensional design matrix. After estimating (3.9) the OLS estimator of the orthogonal match effect is achieved by,

$$\hat{\phi} = W - X\hat{\beta} - D\hat{\theta} - F\hat{\psi} \quad (3.10)$$

$$\bar{\phi}_{ij} = T_{ij}^{-1} \sum_t \hat{\phi}_{ijt} \quad (3.11)$$

where $\hat{\phi}$ is the vector of residuals of the OLS regression in (3.9). $\bar{\phi}_{ij}$ is the mean of $\hat{\phi}$ for individual i at firm j . Therefore the estimate of the orthogonal match effect is given by $\bar{\phi}_{ij}$ which is constant within each individual-firm pair. To summarize, using the orthogonal match fixed effect methodology I estimate the individual fixed effect $\hat{\theta}$, the firm fixed effect, $\hat{\psi}$, and the individual-firm match fixed effect $\bar{\phi}_{ij}$. In the next section I merge these estimated orthogonal fixed effects with the individual mobility data to test the predictions of individual mobility and entrepreneurship.

3.5.5 Mobility Regression

After estimating the orthogonal fixed effects I merge them with the individual mobility data and include them as regressors in the second structural model. The mobility equations are as follows,

$$y_{ijt}^m = x_{i(j)t}\beta + \hat{\theta} + \hat{\psi} + \bar{\phi}_{ij} + e_{ijt} \quad (3.12)$$

$$y_{ijt}^e = x_{i(j)t}\beta + \hat{\theta} + \hat{\psi} + \bar{\phi}_{ij} + e_{ijt} \quad (3.13)$$

where y_{ijt}^m and y_{ijt}^e are dummy variables that capture the mobility of individuals. For investigating turnover y_{ijt}^m takes a value of 1 if an employee switches between firms in the subsequent year, $t + 1$, and 0 otherwise. For investigating entrepreneurial transition y_{ijt}^e takes a value of 1 if an employee forms a spinoff firm in the subsequent year, $t + 1$, and 0 otherwise. The coefficients of estimated orthogonal fixed effects, $\hat{\theta}$, $\hat{\psi}$, and $\bar{\phi}_{ij}$, capture the effects of person, firm, and match fixed effects. Since equations (3.12) and (3.13) are non-linear we use a link function and therefore the appropriate structure of

the mobility equations will be,

$$P[y_{ijt}^m, y_{ijt}^e = 1] = \Lambda[x_{i(j)t}\beta + \hat{\theta} + \hat{\psi} + \bar{\phi}_{ij}] \quad (3.14)$$

where the link function Λ has the logistics distribution.

3.6 Results

Descriptive Statistics are reported in table 3.2. Mean mobility in the Swedish economy between 1995 and 2008 (turnover) is 0.116 or approximately 12%. The next six variables in table 2 show the summary statistics for entrepreneurship at its various definitions. In general, mean transition to entrepreneurship from wage work (self-employment and incorporated entrepreneurship combined) is approximately 0.6%. Out of this fraction approximately 60% of transitions are to self-employment (0.4% in general) and the remaining 40% are to incorporated entrepreneurship. Conditional on mobility, however, the mean number of switches to entrepreneurship as opposed to other established firms is about 4.4%. Out of this fraction nearly 70% depart to self employment (3.2% in general) and the remaining 30% form incorporated startups. The last three variables in table 3.2 show the summary statistics of the estimated individual, firm, and match fixed effects.

As described in the methodology section the estimates of the individual, firm, and match fixed effects are obtained from the residual of the earnings regression, table 3.5. Earnings are defined as raw wages for paid employees and sum of raw wages and capital gains for firm owners. I include dummy variable for ownership in all models to distinguish paid employees from firm owners or any partnership status of the individual. Column 1 shows the estimates of the earnings equation based on individual fixed effects regression, column 2 repeats the same regression with firm fixed effects, and column 3 shows the wage regression using employment spells as fixed effect. The employment spell fixed effects regression in column 3 achieves the highest R^2 among the other models (about 80%) indicating that matching between an employee and the employer is an important

component of individual wages. The estimates of the individual, firm, and match fixed effects are obtained from the 3rd model as described in the methodology section.

Table 3.3 shows Pearson correlation coefficients between various dependent variables and independent variables. There is no serious colinearity between the main independent variable in this study (match effect) and other covariates.

Before proceeding to test the predictions of the model I first revisit the predictions of the matching theory (Jovanovic, 1979b) on turnover. Jovanovic's matching theory predicts that the quality of the employer-employee match is negatively related to switching firms. Table 3.6 reports the result of the logit regression of employee turnover on estimated individual, firm, and match effects. The coefficient of the estimated match effect is negative and highly significant indicating that the quality of the employer-employee match reduces the likelihood of employee turnover. The odds ratio of match effect is 0.96 meaning that a one standard deviation increase in match quality reduces the odds of turnover by 4%. The results of this exercise confirms the standard prediction of the matching literature and also shows that the effect of match quality is substantially high and approximately in par with individual and firm effects. Graphically, keeping all the other covariates at their mean, the marginal effect of match quality on the probability of switching employers is shown in figure 1. The probability of turnover declines sharply from 40% for individuals with lowest match quality to almost zero for those with the highest match quality.

I now turn to investigate the relationship between matching and entrepreneurship. Table 3.7 reports the results of a logit regression of employee entrepreneurship. Columns 1 and 3 show unconditional entrepreneurship where the comparison is made between employees who transition to entrepreneurship and those who stay with their current firm in the subsequent year. Columns 2 and 4 show the transitions conditional on mobility. Not surprisingly the linear effect of match quality appears negative and highly significant in model 1 (unconditionally) and positive but insignificant in model 2 (conditional on

mobility). Hypothesis 1 predicts that both employees with high match quality and low match quality (mismatched employees) are more likely to transition to entrepreneurship than employees with moderate level of match quality. Since match quality is constant within an employment spell in order to investigate the bimodal pattern of transition to entrepreneurship I create four dummy variable pertaining to the quartiles of the distribution of match quality. Model 3 shows the results of the logit regression of unconditional employee entrepreneurship with respect two quartiles of the match quality. Second quartile (25% to 50%) is the omitted category. The results show that individuals belonging to the first quartile as well as the 3rd and 4th quartile are more likely to unconditionally transition to entrepreneurship compared to the 2nd quartile of match quality. This confirms the prediction of the model that mismatched employees and well matched employees are more likely to transition to entrepreneurship. The estimated magnitudes of the transition probabilities are larger at the first ($\beta=0.62$) and fourth quartile ($\beta=0.53$) compared to the third quartile ($\beta=0.19$).

In the next exercise I investigate the quality of entrepreneurial firms. In particular I break down entrepreneurship into self-employment (forming a sole proprietorship startup) and incorporated startups. I test the relation between match quality and transition to self-employment versus incorporated startups. The results of this exercise shall provide support for hypothesis 2. Table 3.8 reports the results of a logit specification of the entrepreneurial transition by type. Dependent variable in model 1 is a dummy that denotes transition to self-employment from wage work. The coefficient of the match fixed effect is negative and statistically significant indicating that as the quality of the match increases transition to self-employment declines. In other words mismatched employees are more likely to transition to self-employment from wage work than to stay with their employer. Model 2 investigates self-employment transition conditional on mobility the coefficient of match quality is negative ($\beta = -0.0508$) and statistically significant at 5% level. This result suggests that conditional on mobility increase in match quality is as-

sociated with switching to other employers than moving to self-employment. A different interpretation is that conditional on mobility mismatched individuals are more likely to transition to self-employment than to switch firms. In models 3 and 4 I investigate transitions to form incorporated startups. The dependent variable in model 3 is unconditional transition to form an incorporated startup where the comparison is made between stayers and movers to form incorporated startups. The coefficient of match effect is positive and statistically significant at 5% level ($\beta=0.0341$). This result suggests that as the quality of the match increases the likelihood of transition to form an incorporated startup increases as well. Model 4 investigates the same relationship conditional on mobility where the comparison is made between movers to other employers and movers to form incorporated startups. Again the coefficient of match effect is positive and statistically significant ($\beta=0.0529$) suggesting that conditional on mobility increase in match quality is associated with forming incorporated startups than moving to other established firms. The results provide support for hypothesis 2 that increase in match quality is associated with forming higher quality businesses. In addition the combined results of models 1 through 4 further illustrates the bimodal pattern of transition to entrepreneurship where transitions in the lower tail of distribution of match quality is associated with self-employment and transitions in the upper tail of the distribution of match quality is associated with forming incorporated businesses. Figures 2 and 3 depict the predicted probabilities of entrepreneurial transitions to incorporated startups and self-employment respectively with match quality keeping the values of covariates at their means.

To investigate further the relationship between matching and entrepreneurial transition I examine whether or not departing employees start a business in the same industry of their prior employer (forming intra-industry spinoffs) given their match quality. Table 3.11 shows the results of this exercise. The first 2 columns show the relationship between matching and mobility to the same industry class. The sample is limited to all

movers and the dependent variable is a dummy that takes a value of 1 if the industry of the destination and the current employing firm is similar. The coefficient of match effect is positive and significant (mobility to the same 2 digit industry class: $\beta=0.0303$, mobility to the same 3 digit industry class: $\beta=0.0317$). This further confirms the predictions of the matching theory suggesting that match quality is positively related to remaining in the same industry in case of mobility or conversely mismatching is positively related to exiting the focal industry in case of mobility. Models 3 and 4 show the results of intra-industry transition to entrepreneurship at the same 2 and 3 digit industry classification of the prior employer. The sample in this case is limited to all entrepreneurs (both self employed and founders of incorporated startups) and comparison is made between them. In both models the coefficient of match effect is positive and statistically significant at 1% level (entrepreneurship in the same 2 digit industry class: $\beta=0.031$, entrepreneurship in the same 3 digit industry class: $\beta=0.0308$). This result suggest that among entrepreneurs who were previously employed at established firms the larger their match quality is the larger the likelihood of starting their business in the same industry classification of their parent firm. This confirms hypothesis 4.

Next I investigate the predictions of matching on team entrepreneurship in table 3.12. Similar to the previous analysis the sample only consists of employees who transition to entrepreneurship. I define team entrepreneurship in two ways: (1) when a founder takes a team of employees from her prior employer to found a new firm, and (2) when a team of founders leave their prior employers to found a new firm. In the second case I eliminate all the non-founder employees from the definition. With these two definitions I create two dummy coded dependent variables taking a value of 1 when the team size is more than 1 and 0 otherwise. The dependent variable in model 1 is a dummy pertaining to the first definition of team entrepreneurship. The coefficient of match effect is positive and statistically significant ($\beta=0.088$) suggesting that match quality is positively associated with founding a firm with a team of employees from the prior employer. Model 2 repeats

the same analysis, however, with the second definition of team entrepreneurship. Again the coefficient of match quality is positive and statistically significant ($\beta=0.067$). Models 3 and 4 repeat the same analysis with two definitions of team entrepreneurship with the exception that the sample is now limited to founding only incorporated startups. Model 3 uses the first definition of team entrepreneurship. The coefficient of match quality is positive and statistically significant ($\beta=0.093$). This suggests that among entrepreneurs who found incorporated businesses forming the firm with a team of prior employees is positively related to the match quality of the founder with her prior employer. Model 4 repeats the same analysis with the second definition of team entrepreneurship. The coefficient of match quality is positive but smaller and it is only significant at 10%. All together the results in table 19 confirms the prediction of hypothesis 3.

3.7 Robustness Checks

In this section I perform a number of robustness checks. First concern is about the real distinction between self-employment and incorporated startups. Since the minimum share capital requirement to form an incorporated business in Sweden is about \$8000, it seems that there is a minimal distinction between the two, besides book keeping regulations, in terms of their growth orientation. To investigate whether sole-proprietorship businesses and incorporated businesses differ in their growth orientation I investigate the difference in their gross capital investments (e.g. in machinery, equipment, and plants) during the first year of their operation. Table 3.13 shows the summary statistics of the amount that entrepreneurs invest during the first year of their business by their incorporation status of their business. The mean amount of investment by entrepreneurs who found incorporated startups is roughly 5 times higher than that of the self employed entrepreneurs. The histogram of the log of gross investment during the first year of business operation in figure 4 also shows a slightly skewed distribution for self employed individuals. To confirm the descriptive statistics in mean differences I investigate the relationship be-

tween the amount of investment and incorporation status of entrepreneurs' business in a formal regression framework. Table 3.14 reports the result of the OLS regression of the log gross investment in the first year of business on Incorporation status of the business. The regression equation includes control variables for demographic characteristics of the founders in the first year of business formation, their wage at their prior firm to proxy for their income prior to the business formation, and the size of their startup firm proxied by the number of employees during the first year of operation. The model also includes dummy variables for the year, industry, and the geographic location of the startup. The effect of incorporation status is positive and significant implying that forming an incorporated business is associated with 112% change in the mean of business investment during the first year of operation. Therefore incorporation status appears to have a meaningful effect on business investments and perhaps growth orientation of startups.

As a further robustness check for the main predictions regarding mobility and transition to entrepreneurship I embed all four occupational choices of individuals (staying with the current employer, moving to a different established firm, transition to self employment, and forming an incorporated startup) in one framework and investigate the relationship with match quality in a multinomial logit setting. A critical assumption of the multinomial logit specification is the independence of irrelevant alternatives. I check for the independence of all four choices using Hausman and McFadden's (1984) specification test. The null hypothesis that the outcomes are independent from each other can not be rejected. The results of the multinomial logit regression are reported in table 3.9. All models report odds ratios. Similar to logit specifications the effect match quality on mobility and self employment is negative. The effect of match quality on forming an incorporated startup is positive. The magnitude of the effects are similar to those reported in the logit models. In table 3.10 I report the results of the multinomial logit model when the base outcome is mobility to a different employer. Similar to earlier

findings increase in match quality is associated with choosing incorporated startup over moving to a different employer.

With respect to team entrepreneurship I check for two issues that might bias the results. First in the data the initial team size ranges from the minimum of 1 to a maximum of 129. Because these new entities might be formed by divestiture of existing firms I limit the definition of team to no more than 20 employees. Therefore I only limit the analysis of team entrepreneurship to those firms formed with less than or equal to 20 employees from the previous employer of the founder. The results of the team entrepreneurship hypothesis remains the same: As the match quality increases the likelihood of forming a new firm with a team of employees from the prior employer increases as well. The second issue relates to the double counting in the definition of team entrepreneurship. If a new firm is founded by two or more founders from their prior employer then in the regression framework for one startup firm there would be three observation on match quality coming from the three founders contribute to the prediction of team entrepreneurship. To mitigate the bias in predictions associated with multiple counts of the same firm I keep the observation of the founder with highest match quality as the principal founder of the startup and discard the observations coming from the other founders for the same startup firm. I run the regressions of team entrepreneurship with this constraint and the results remain the same.

3.8 Conclusion

In this paper I relate matching in the labor market to the entrepreneurial transition of employees from paid employment. The matching theory in labor economics does not elaborate on the labor market outcomes of employees beyond turnover and wage growth. To completely understand the consequences of matching on the labor market outcomes of employees I embed entrepreneurship into the turnover process. I develop a simple model of entrepreneurship based on balanced skills and matching. The key feature of

the model is that the quality of the match determines the type of skills that employees imbibe in paid employment namely general versus specific skills both of which might be relevant for entrepreneurship. High match quality implies greater incentives to invest in firm specific skills which in turn can be appropriated by individuals to form spinoff companies. Low match quality implies greater incentives to invest in general skills which not only can be used in other firms but it is also relevant for entrepreneurship.

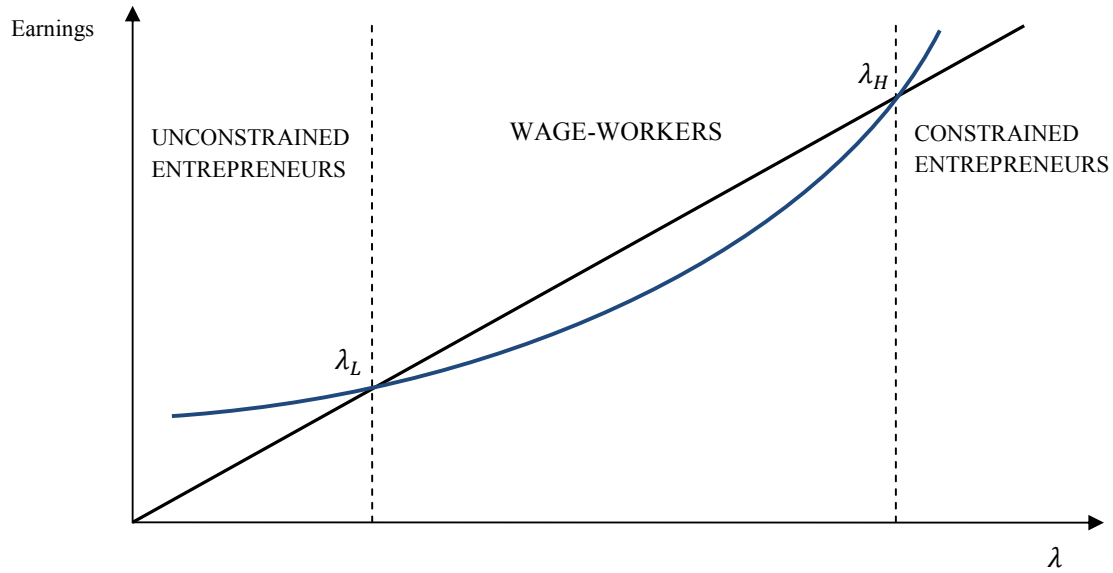
Entrepreneurs with different match quality differ in the types of spinoff companies that they found. Mismatched employees are more likely to found sole-proprietorship spinoffs whereas high match quality employees are more likely to found incorporated spinoffs. The distinction between these two types of entrepreneurial transitions is interesting and is consistent with the theoretical arguments about the nature of the skill sets and outside employment opportunities. General skill sets that mismatched employees acquire on the job, although relevant for entrepreneurship, is likely to have low depth that is not suitable to found growth oriented companies. On the contrary specific skill sets of well matched employees may have enough depth to found growth oriented companies.

In addition matching framework gives additional predictions on the characteristics of the spinoffs. First differences in the skill sets of employees with different match quality determine the industry in which the spinoff firm is formed. Since high match quality employees imbibe greater industry specific skills they are more likely to found their spinoff firm in the same industry as their prior employer compared to employees with lower match quality. Second, team entrepreneurship increases with the quality of the match. The key mechanism is that in order to form a spinoff firm high match quality employees incur higher adjustment costs to balance their skills. One way of balancing the skill set is to form a team. Therefore employees with high match quality are more likely to found a spinoff firm with a group of coworkers than employees with low match quality.

Overall this study suggests that matching in the labor market determines the labor

market outcomes of employees beyond mobility to other incumbent firms. The quality of the match has a substantial effect on the entrepreneurial outcomes of employees as well. This study suggest that, from the firms' perspective, there is a dark side of matching. Contrary to the conventional arguments that firms benefit from high quality matches because of lower threats of mobility, high quality matches might terminate to form a competing firm, in the same industry, and with a group of colleagues.

Figure 1: Match Quality and Earnings



Note: blue curve represents earnings associated with entrepreneurship whereas the solid 45° line represents earnings in wage work. Individuals whose match quality is above the cut-off λ_H are constrained in the skill mix required for entrepreneurship. They will incur a cost to balance their skill mix. Individuals whose match quality is below the cut-off λ_L are unconstrained entrepreneurs meaning that they have a balanced skill. These individuals are mismatched with their prior employer and invest in general skills.

Table 3.1: Variable Names and Descriptions

Variables	Code	Description
<i>Independent Variables</i>		
Female	FEMALE	This variable is a dummy that takes a value of 1 for females and 0 for males.
Swedish Background	SWED_BKG	This variable is a dummy that takes a value of 1 if the individual was born in Sweden with at least one Swedish born parent. It takes a value of 0 for individuals born outside of Sweden or born in Sweden from two foreign parents.
Age	AGE	Denotes the age of the individual.
Tenure	TENURE	Denotes the tenure of the individual in her current firm.
Education ≤ 11 Years	EDUCATION_G1	This variable is a dummy that takes a value of 1 for individuals having less than or equal to 11 years of education and 0 otherwise.
Education =12 Years	EDUCATION_G2	This variable is a dummy that takes a value of 1 for individuals having exactly 12 years of education and 0 otherwise.
Education $>12, \leq 15$ Years	EDUCATION_G3	This variable is a dummy that takes a value of 1 for individuals having more than 12 and less than or equal to 15 years education and 0 otherwise.
Education >15 Years	EDUCATION_G4	This variable is a dummy that takes a value of 1 for individuals having more than 15 years education and 0 otherwise.
Individual Effect	IND_FX	This is the estimated individual fixed effect from the wage regression. It denotes the constant (stable) quality of the individual affecting her wage.
Firm Effect	FRM_FX	This is the estimated firm fixed effect from the wage regression. It denotes the constant (stable) quality of the firm affecting all employees' wages.
Match Effect	MATCH_FX	This is the estimated match fixed effect from the wage regression denoting the quality of the employer-employee match. It is the component of an individual's wage that is fixed within her match.
<i>Dependent Variables</i>		
Mobility	MOBIL	This is a dummy variable that takes a value of 1 if the individual moves to a different employer in $t + 1$ and 0 if she stays with her current employer in $t + 1$.

Table 3.1: Variable Names and Descriptions

Variables	Code	Description
Unconditional entrepreneurship	En- ENTREP_UNCOND	This is a dummy variable that takes a value of 1 if the individual transitions to entrepreneurship (either self-employment or forming an incorporated spinoff) in $t+1$ and 0 if she stays with her current employer in $t + 1$. Note that the comparison group are individuals who do not switch firms between t and $t + 1$, hence denoting entrepreneurship unconditional to mobility.
Conditional entrepreneurship	En- ENTREP_COND	This is a dummy variable that takes a value of 1 if the individual transitions to entrepreneurship (either self-employment or forming an incorporated spinoff) in $t + 1$ and 0 if she switches to another established employer in $t + 1$. Note that the comparison is among individuals who switch firms between t and $t + 1$, hence denoting entrepreneurship conditional on mobility.
Unconditional Self Employment	SELFEMP_UNCOND	This is a dummy variable that takes a value of 1 if the individual transitions to self-employment (forming a sole proprietorship business) in $t + 1$ and 0 if she stays with her current employer in $t + 1$. Note that the comparison group are individuals who do not switch firms between t and $t + 1$, hence denoting self-employment unconditional to mobility.
Conditional Self Employment	SELFEMP_COND	This is a dummy variable that takes a value of 1 if the individual transitions to self-employment (forming a sole proprietorship business) in $t + 1$ and 0 if she switches to another established employer in $t + 1$. Note that the comparison is among individuals who switch firms between t and $t + 1$, hence denoting self-employment on mobility.

Table 3.1: Variable Names and Descriptions

Variables	Code	Description
Unconditional Incorporated Entrepreneurship	ENTREP_INC_UNCOND	This is a dummy variable that takes a value of 1 if the individual transitions to form an incorporated spinoff in $t + 1$ and 0 if she stays with her current employer in $t + 1$. Note that the comparison group are individuals who do not switch firms between t and $t + 1$, hence denoting incorporated entrepreneurship unconditional to mobility.
Conditional Incorporated Entrepreneurship	ENTREP_INC_COND	This is a dummy variable that takes a value of 1 if the individual transitions to form an incorporated spinoff in $t + 1$ and 0 if she switches to another established employer in $t + 1$. Note that the comparison is among individuals who switch firms between t and $t + 1$, hence denoting incorporated entrepreneurship conditional on mobility.
Team Entrepreneurship (Employees)	TEAM_EMP	This variable pertains to the first definition of team entrepreneurship: when a founder takes a team of employees from her prior employer to found a new firm. It is a dummy coded variable taking a value of 1 when at least one employee from the prior employer accompanies the founder to a new startup and 0 otherwise. This definition of team entrepreneurship represents a broad characterization of team entrepreneurship.
Team Entrepreneurship (Founders)	TEAM_FNDR	This variable pertains to the second definition of team entrepreneurship: when a team of founders leave their prior employers to found a new firm. It is a dummy coded variable taking a value of 1 when more than 1 founders leave their common prior employer to start a new firm. This definition of team entrepreneurship represents a narrow and restrictive characterization of team entrepreneurship because it does not take into account the number of employees who accompany the founders to the startup.

Table 3.1: Variable Names and Descriptions

Variables	Code	Description
Intra-Industry Mobility	INTRA_MOB	This is a dummy variable that takes a value of 1 if the individual moves to the same industry upon mobility at $t + 1$ compared to her prior industry at t and 0 if the two consecutive industries are different. The similarity is measured for 2 and 3 digit of the Swedish Standard Industrial Classification.
Intra-Industry entrepreneurship	En- INTRA_ENT	This is a dummy variable that takes a value of 1 if the individual start a new firm in the same industry at $t + 1$ compared to the industry of her prior employer at t and 0 if the two consecutive industries are different when an employee transitions to entrepreneurship from wage work .

Table 3.2: Descriptive Statistics

	mean	sd	min	max
Mobility	0.116	0.320	0.000	1.000
Unconditional Entrepreneurship	0.006	0.076	0.000	1.000
Conditional Entrepreneurship	0.044	0.206	0.000	1.000
Unconditional Self Employment	0.004	0.065	0.000	1.000
Conditional Self Employment	0.032	0.177	0.000	1.000
Unconditional Incorporated Entrepreneurship	0.002	0.039	0.000	1.000
Conditional Incorporated Entrepreneurship	0.012	0.109	0.000	1.000
Age	40.936	9.084	20.000	59.000
Female	0.309	0.462	0.000	1.000
Swedish Background	0.900	0.300	0.000	1.000
Education ≤ 11 Years	0.583	0.493	0.000	1.000
Education =12 Years	0.183	0.387	0.000	1.000
Education $>12, \leq 15$ Years	0.230	0.421	0.000	1.000
Education >15 Years	0.004	0.061	0.000	1.000
Earnings	271676.224	195425.353	0.000	28317952.000
Tenure	7.801	5.437	1.000	22.000
Firm Age	10.799	5.648	1.000	22.000
Employer's Nr. of Employees	1893.590	5193.287	1.000	42682.000
Employer's Average Wage	253912.926	99573.675	1.000	13354328.000
Nr. of Establishments >1	1.496	0.500	1.000	2.000
Individual Effect	0.053	0.530	-12.208	10.037
Firm Effect	3.183	0.375	-9.947	15.041
Match Effect	0.005	0.151	-6.388	5.206
Observations	3820049			

Table 3.3: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
(1) Mobility	1.00														
(2) Unconditional Entrepreneurship		1.00													
(3) Conditional Entrepreneurship			1.00												
(4) Unconditional Self Employment				1.00											
(5) Conditional Self Employment					1.00										
(6) Unconditional Incorporated Entrepreneurship						1.00									
(7) Conditional Incorporated Entrepreneurship							1.00								
(8) Age	-0.11	-0.01	0.03	-0.02	0.02	-0.00	0.04	1.00							
(9) Female	-0.01	-0.01	-0.03	-0.01	-0.02	-0.01	-0.03	-0.01	1.00						
(10) Swedish Background	0.00	-0.00	-0.00	-0.00	-0.01	0.00	0.01	-0.02	-0.03	1.00					
(11) Education ≤ 11 Years	-0.05	-0.01	0.00	-0.01	0.01	-0.01	-0.01	0.07	-0.06	-0.01	1.00				
(12) Education =12 Years	0.02	0.00	-0.01	0.00	-0.01	0.00	-0.00	-0.09	0.07	-0.00	-0.56	1.00			
(13) Education $>12, \leq 15$ Years	0.04	0.01	0.00	0.00	-0.01	0.01	0.02	-0.01	0.01	0.02	-0.65	-0.26	1.00		
(14) Education >15 Years	-0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	0.02	-0.01	-0.01	-0.07	-0.03	-0.03	1.00	
(15) Earnings	-0.01	-0.00	-0.01	-0.01	-0.03	0.02	0.04	0.18	-0.19	0.04	-0.23	-0.02	0.28	0.08	1.00
(16) Tenure	-0.18	-0.03	0.03	-0.03	0.02	-0.02	0.02	0.36	-0.00	0.00	0.13	-0.05	-0.10	-0.01	0.04
(17) Firm Age	-0.07	-0.02	0.00	-0.01	0.00	-0.01	-0.00	0.13	-0.01	0.01	0.01	-0.01	-0.00	0.00	0.09
(18) Nr. of Employees	-0.06	-0.02	-0.03	-0.02	-0.02	-0.01	-0.02	0.05	0.08	-0.02	-0.01	0.01	0.01	0.01	-0.01
(19) Employer's Average Wage	-0.01	-0.01	-0.01	-0.01	-0.02	0.16	0.02	-0.07	0.03	-0.23	0.01	0.26	0.05	0.54	0.08
(20) Nr. of Establishments >1	-0.07	-0.04	-0.06	-0.03	-0.04	0.01	-0.04	0.06	0.07	-0.01	-0.07	0.01	0.07	0.02	0.08
(21) Individual Effect	0.02	-0.00	-0.02	-0.01	-0.04	0.01	0.02	-0.40	0.02	-0.02	0.15	-0.02	-0.15	-0.04	0.21
(22) Firm Effect	-0.03	-0.02	-0.04	-0.02	-0.04	-0.01	-0.02	0.00	-0.02	0.00	-0.07	0.00	0.07	0.02	0.18
(23) Match Effect	-0.01	-0.00	0.00	-0.00	0.00	0.00	0.00	-0.00	-0.01	-0.00	0.00	-0.00	-0.00	-0.00	0.11
Observations	3820049														

	16	17	18	19	20	21	22	23
(16) Tenure	1.00							
(17) Firm Age	0.29	1.00						
(18) Nr. of Employees	0.03	-0.04	1.00					
(19) Employer's Average Wage	0.16	-0.00	0.00	1.00				
(20) Nr. of Establishments >1	0.13	0.12	0.35	0.16	1.00			
(21) Individual Effect	-0.07	0.02	-0.05	0.09	-0.04	1.00		
(22) Firm Effect	0.03	0.06	0.04	0.31	0.15	-0.40	1.00	
(23) Match Effect	-0.01	0.01	-0.01	0.01	-0.00	-0.06	-0.03	1.00
Observations	3820049							

Table 3.5: OLS Regression of Log Earnings

	(1)	(2)	(3)
Age Squared	0.000149*** (0.0000342)	0.000758*** (0.00000389)	0.00103*** (0.0000515)
Age Cubed	-0.00000688*** (0.000000282)	-0.0000116*** (6.37e-08)	-0.0000108*** (0.000000435)
Tenure Squared	0.000207*** (0.0000274)	0.000426*** (0.0000275)	-0.000120 (0.0000628)
Tenure Cubed	-0.0000175*** (0.00000134)	-0.0000161*** (0.00000142)	-0.00000517* (0.00000241)
Age Squared X Education	0.0000938*** (0.00000287)	0.0000920*** (0.00000125)	0.000292*** (0.00000915)
Age Cubed X Education	-0.000000654*** (4.76e-08)	-0.000000348*** (2.41e-08)	-0.00000315*** (0.000000116)
Tenure Squared X Education	-0.000152*** (0.0000151)	-0.000373*** (0.0000148)	-0.0000321 (0.0000336)
Tenure Cubed X Education	0.0000103*** (0.000000750)	0.0000150*** (0.000000784)	0.00000427** (0.00000133)
Female		-0.365*** (0.000647)	
Swedish Background		0.0755*** (0.000907)	
Individual Fixed Effect	✓		
Firm Fixed Effect		✓	
Spell Fixed Effect			✓
Observations	4071144	4071144	4071144
R^2	0.621	0.489	0.796

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Logit Regression of Employee Turnover. DV: Mobility

	(1) Model 1	(2) Model 2
Female	-0.126*** (0.00385)	-0.125*** (0.00386)
Swedish Background	0.0324*** (0.00559)	0.0272*** (0.00560)
Age	-0.0222*** (0.000207)	-0.0289*** (0.000239)
Tenure	-0.0971*** (0.000406)	-0.0963*** (0.000406)
Education ≤ 11 Years	-0.0395*** (0.00446)	-0.00408 (0.00451)
Education $> 12, \leq 15$ Years	0.0721*** (0.00501)	0.0601*** (0.00503)
Education > 15 Years	-0.0771** (0.0283)	-0.108*** (0.0284)
Individual Effect		-0.121*** (0.00215)
Firm Effect		-0.120*** (0.00186)
Match Effect		-0.0404*** (0.00139)
Constant	0.915*** (0.0325)	1.133*** (0.0329)
Observations	3820047	3820047
Pseudo R^2	0.073	0.075
Log Likelihood	-1270223.4	-1267464.3
χ^2	198733.0	204251.3
P-value	0	0

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7: Logit Regression of Employee Entrepreneurship.

	(1) Unconditional Entrepreneurship	(2) Entrepreneurship Conditional on Mobility	(3) Unconditional Entrepreneurship	(4) Entrepreneurship Conditional on Mobility
Female	-0.477*** (0.0186)	-0.377*** (0.0189)	-0.466*** (0.0186)	-0.371*** (0.0190)
Swedish Background	-0.0406 (0.0244)	-0.0535* (0.0250)	-0.0599* (0.0245)	-0.0401 (0.0251)
Age	-0.0352*** (0.00103)	-0.00608*** (0.00107)	-0.0354*** (0.00103)	-0.00615*** (0.00107)
Tenure	-0.0636*** (0.00167)	0.0310*** (0.00164)	-0.0405*** (0.00187)	0.0251*** (0.00164)
Education ≤ 11 Years	0.0269 (0.0201)	0.00879 (0.0206)	0.0339 (0.0201)	-0.00135 (0.0207)
Education $> 12, \leq 15$ Years	0.0825*** (0.0222)	0.0771*** (0.0228)	0.0765*** (0.0222)	0.0992*** (0.0229)
Education > 15 Years	-0.0109 (0.121)	0.183 (0.125)	0.0138 (0.121)	0.183 (0.125)
Individual Effect	-0.246*** (0.00803)	-0.118*** (0.00864)	-0.254*** (0.00804)	-0.104*** (0.00865)
Firm Effect	-0.181*** (0.00536)	-0.0661*** (0.00551)	-0.187*** (0.00539)	-0.0480*** (0.00553)
Match Effect	-0.0327*** (0.00652)	0.000420 (0.00471)		
Match Effect 1st Quartile			0.625*** (0.0241)	-0.899*** (0.0246)
Match Effect 3rd Quartile			0.198*** (0.0247)	-0.0420 (0.0264)
Match Effect 4th Quartile			0.531*** (0.0244)	-0.945*** (0.0248)
Constant	-2.498*** (0.122)	-3.325*** (0.121)	-2.915*** (0.124)	-2.673*** (0.122)
Observations	3396146	442420	3396146	442420
Pseudo R^2	0.068	0.053	0.071	0.068
Log Likelihood	-112231.8	-75854.0	-111836.2	-74655.6
χ^2	16261.3	8528.2	17052.5	10925.2
P-value	0	0	0	0

Standard errors in parentheses.

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies. Unconditional entrepreneurship is a dummy variable that takes a value of 1 if the individual transitions to entrepreneurship (either self-employment or forming an incorporated spinoff) in $t + 1$ and 0 if she stays with her current employer in $t + 1$. Conditional entrepreneurship is a dummy variable that takes a value of 1 if the individual transitions to entrepreneurship (either self-employment or forming an incorporated spinoff) in $t + 1$ and 0 if she switches to another established employer in $t + 1$.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8: Logit Regression of Employee Entrepreneurship.

	(1) Unconditional Employment	Self- Self-Employment Conditional on Mobility	(2) Unconditional Incorporated Spinoff	(3) Unconditional Incorporated Spinoff	(4) Incorporated Conditional Spinoff on Mobility
Female	-0.385*** (0.0213)	-0.246*** (0.0215)	-0.826*** (0.0391)	-0.766*** (0.0396)	
Swedish Background	-0.120*** (0.0277)	-0.149*** (0.0280)	0.268*** (0.0525)	0.270*** (0.0535)	
Age	-0.0467*** (0.00119)	-0.0163*** (0.00122)	-0.000724 (0.00203)	0.0234*** (0.00206)	
Tenure	-0.0662*** (0.00199)	0.0331*** (0.00194)	-0.0574*** (0.00304)	0.0267*** (0.00297)	
Education ≤ 11 Years	0.123*** (0.0232)	0.110*** (0.0237)	-0.293*** (0.0397)	-0.309*** (0.0406)	
Education $> 12, \leq 15$ Years	-0.0123 (0.0264)	-0.0182 (0.0268)	0.340*** (0.0414)	0.324*** (0.0423)	
Education > 15 Years	-0.180 (0.152)	0.0126 (0.154)	0.476* (0.200)	0.636** (0.206)	
Individual Effect	-0.438*** (0.00881)	-0.313*** (0.00942)	0.347*** (0.0176)	0.459*** (0.0174)	
Firm Effect	-0.293*** (0.00663)	-0.161*** (0.00633)	0.111*** (0.0122)	0.188*** (0.0116)	
Match Effect	-0.0508*** (0.00680)	-0.0112* (0.00475)	0.0341* (0.0163)	0.0529*** (0.0119)	
Constant	-1.618*** (0.146)	-2.917*** (0.140)	-6.465*** (0.234)	-6.887*** (0.236)	
N	3390860	442420	3375323	441771	
Pseudo R^2	0.067	0.041	0.127	0.157	
Log Likelihood	-86120.3	-60444.1	-34415.7	-24142.9	
χ^2	12394.3	5209.3	10018.8	9011.6	
P-value	0	0	0	0	

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies. Unconditional self-employment is a dummy variable that takes a value of 1 if the individual transitions to self-employment (forming a sole proprietorship business) in $t + 1$ and 0 if she stays with her current employer in $t + 1$. Self-employment conditional on mobility is a dummy variable that takes a value of 1 if the individual transitions to self-employment (forming a sole proprietorship business) in $t + 1$ and 0 if she switches to another established employer in $t + 1$. Unconditional incorporated spinoff is a dummy variable that takes a value of 1 if the individual transitions to form an incorporated spinoff in $t + 1$ and 0 if she stays with her current employer in $t + 1$. Conditional incorporated spinoff is a dummy variable that takes a value of 1 if the individual transitions to form an incorporated spinoff in $t + 1$ and 0 if she switches to another established employer in $t + 1$.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9: Multinomial Logit Regression of Employee Mobility and Entrepreneurship.

	Base Outcome: Staying with Current Employer		
	Mobility	Self Employment	Incorporated Startup
Female	0.895*** (0.00351)	0.684*** (0.0145)	0.434*** (0.0170)
Swedish Background	1.030*** (0.00589)	0.890*** (0.0246)	1.311*** (0.0687)
Age	0.972*** (0.000237)	0.956*** (0.00113)	0.999 (0.00202)
Tenure	0.907*** (0.000378)	0.938*** (0.00185)	0.944*** (0.00285)
Education ≤ 11 Years	0.995 (0.00457)	1.118*** (0.0259)	0.743*** (0.0294)
Education $>12, \leq 15$ Years	1.060*** (0.00543)	1.002 (0.0264)	1.415*** (0.0585)
Education >15 Years	0.892*** (0.0259)	0.861 (0.131)	1.621* (0.324)
Individual Effect	0.892*** (0.00197)	0.657*** (0.00563)	1.414*** (0.0246)
Firm Effect	0.891*** (0.00172)	0.762*** (0.00451)	1.113*** (0.0135)
Match Effect	0.960*** (0.00136)	0.959*** (0.00579)	1.033* (0.0158)
Constant	3.078*** (0.103)	0.190*** (0.0266)	0.00187*** (0.000436)
<i>N</i>	3820049		
Pseudo R^2	0.075		
Log Likelihood	-1351671.5		
χ^2	218911.2		
P-value	0.000		

Exponentiated coefficients; Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10: Multinomial Logit Regression of Employee Mobility and Entrepreneurship.

	Base Outcome: Mobility to Another Established Firm		
	Staying with the Current Firm	Self Employment	Incorporated Startup
Female	1.117*** (0.00438)	0.765*** (0.0164)	0.485*** (0.0190)
Swedish Background	0.971*** (0.00554)	0.864*** (0.0242)	1.273*** (0.0670)
Age	1.029*** (0.000251)	0.983*** (0.00118)	1.028*** (0.00209)
Tenure	1.103*** (0.000460)	1.035*** (0.00208)	1.041*** (0.00317)
Education ≤ 11 Years	1.005 (0.00462)	1.124*** (0.0264)	0.746*** (0.0297)
Education $>12, \leq 15$ Years	0.943*** (0.00483)	0.945* (0.0252)	1.335*** (0.0554)
Education >15 Years	1.121*** (0.0325)	0.965 (0.148)	1.817** (0.366)
Individual Effect	1.121*** (0.00248)	0.736*** (0.00643)	1.585*** (0.0278)
Firm Effect	1.123*** (0.00217)	0.856*** (0.00512)	1.250*** (0.0153)
Match Effect	1.042*** (0.00147)	0.999 (0.00610)	1.076*** (0.0165)
Constant	0.325*** (0.0109)	0.0616*** (0.00868)	0.000607*** (0.000142)
N	3820049		
Pseudo R^2	0.075		
Log Likelihood	-1351671.5		
χ^2	218911.2		
P-value	0.000		

Exponentiated coefficients; Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.1: Probability of Mobility to an Established Firm with Match Quality

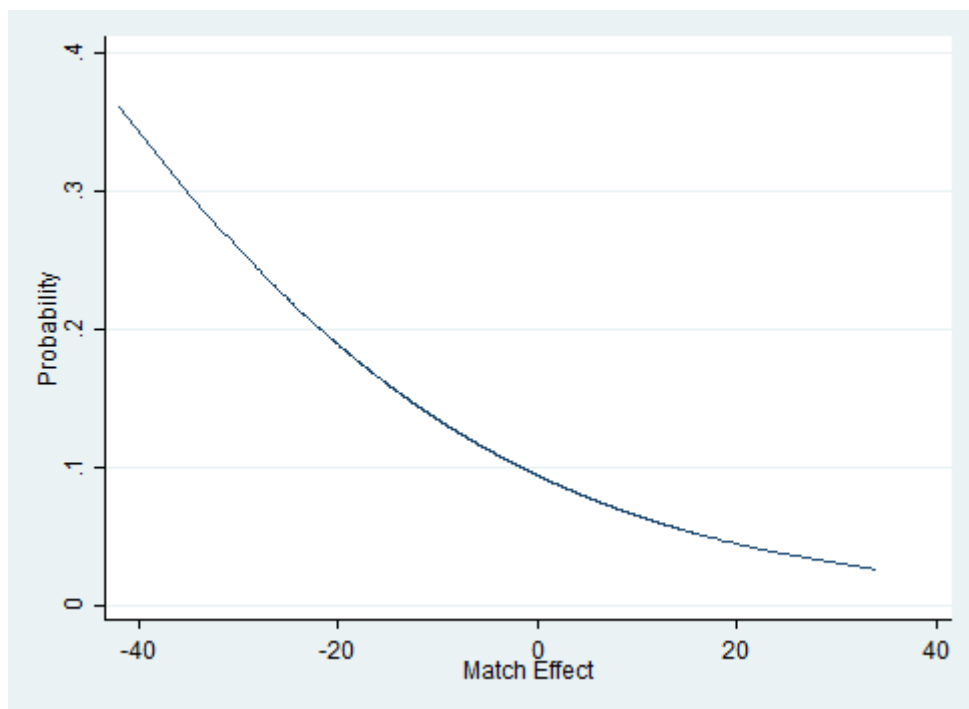
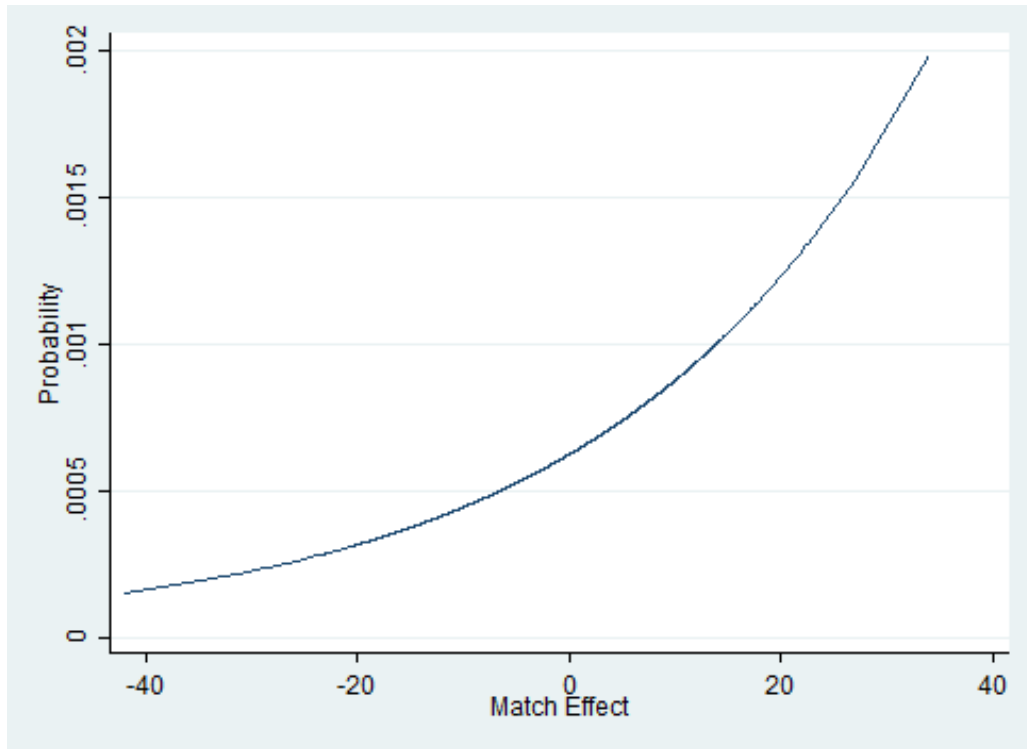
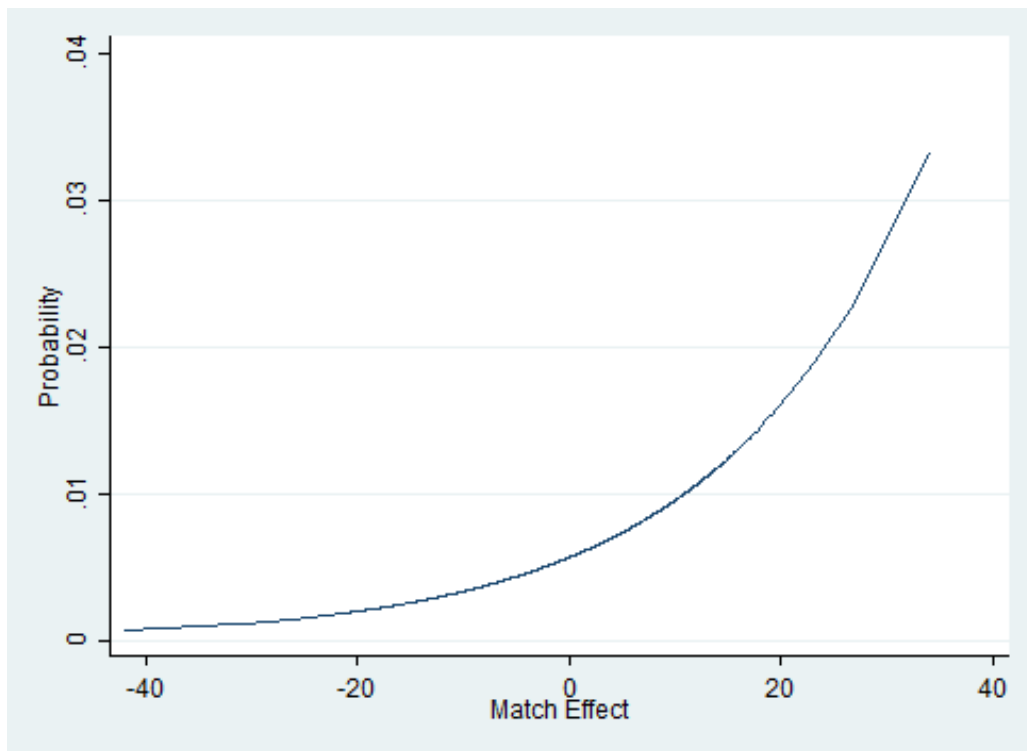


Figure 3.2: Probability of Transition to Incorporated Spinoff with Match Quality

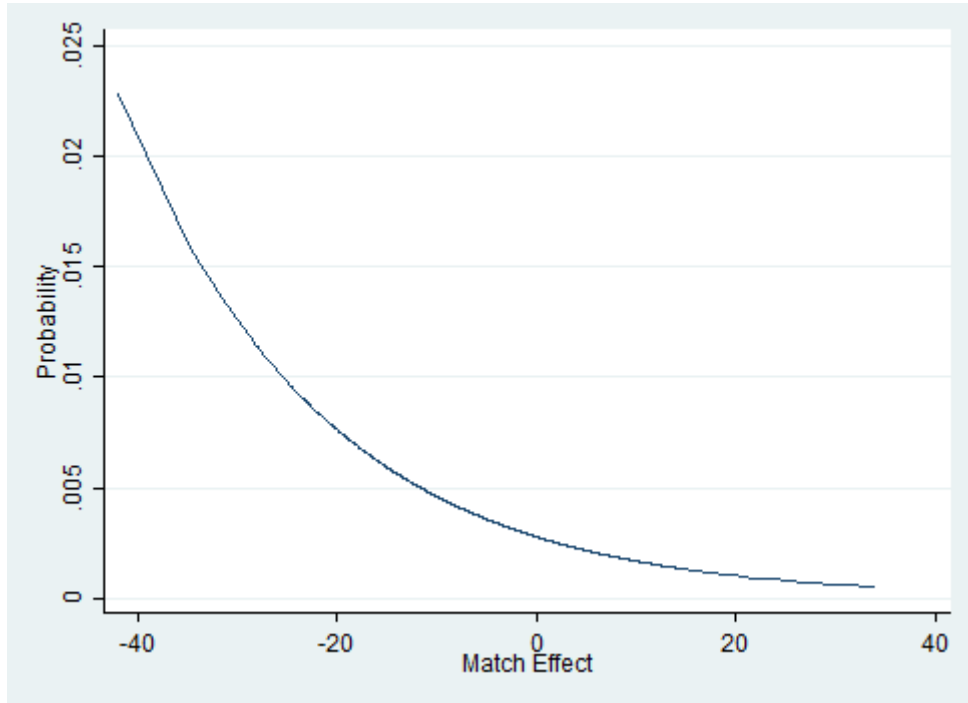


(a) Unconditional Probability of Transition to Incorporated Spinoff

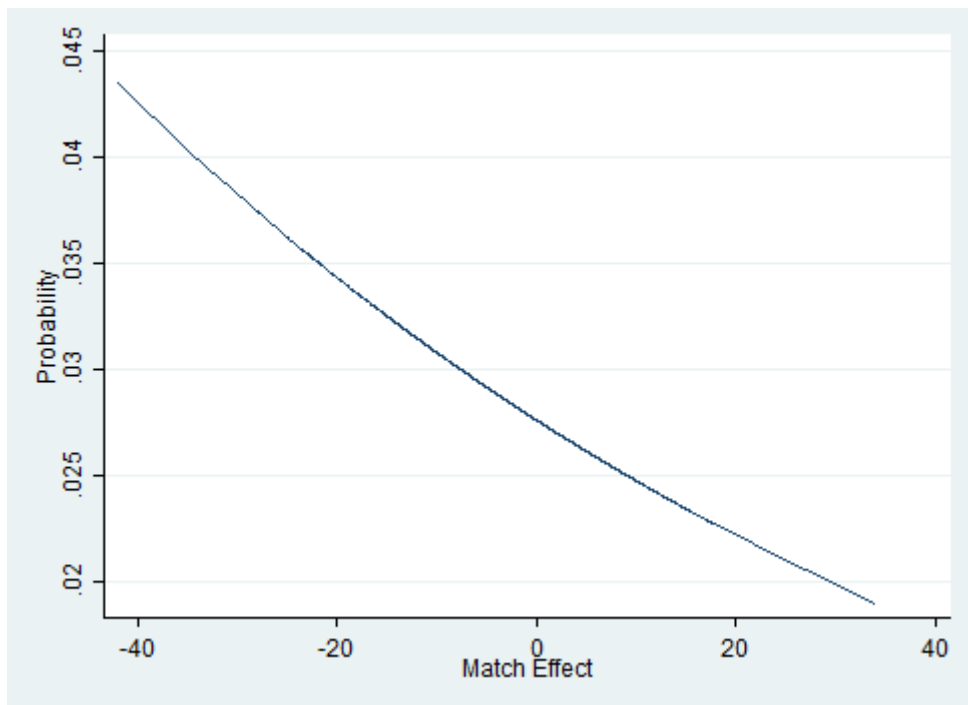


(b) Probability of Transition to Incorporated Spinoff Conditional on Mobility

Figure 3.3: Probability of Transition to Self-Employment with Match Quality



(a) Unconditional Probability of Transition to Self-Employment



(b) Probability of Transition to Self-Employment Conditional on Mobility

Table 3.11: Logit Regression of Intra-Industry Mobility and Entrepreneurship.

	(1)	(2)	(3)	(4)
	Mobility(2 Digit Industry Class)	Mobility(3 Digit Industry Class)	Entrepreneurship(2 Digit Industry Class)	Entrepreneurship(3 Digit Industry Class)
Female	-0.0574*** (0.00741)	-0.0813*** (0.00781)	-0.193*** (0.0436)	-0.231*** (0.0458)
Swedish Background	0.0187 (0.0107)	-0.00336 (0.0112)	-0.0749 (0.0560)	-0.156** (0.0571)
Age	0.0268*** (0.000463)	0.0287*** (0.000485)	0.00125 (0.00244)	0.00320 (0.00252)
Tenure	0.0216*** (0.000768)	0.0231*** (0.000800)	0.0102** (0.00394)	0.0126** (0.00406)
Education ≤ 11 Years	-0.0613*** (0.00866)	-0.0818*** (0.00913)	-0.0628 (0.0465)	-0.0953* (0.0485)
Education $>12, \leq 15$ Years	0.0222* (0.00958)	0.0605*** (0.0101)	0.212*** (0.0522)	0.262*** (0.0538)
Education >15 Years	0.138* (0.0568)	0.275*** (0.0582)	0.101 (0.296)	0.249 (0.295)
Individual Effect	0.187*** (0.00420)	0.195*** (0.00445)	0.198*** (0.0177)	0.200*** (0.0187)
Firm Effect	0.121*** (0.00346)	0.136*** (0.00374)	0.122*** (0.0124)	0.122*** (0.0130)
Match Effect	0.0330*** (0.00200)	0.0317*** (0.00213)	0.0310** (0.0112)	0.0308** (0.0120)
Constant	-4.832*** (0.166)	-4.892*** (0.166)	-2.628*** (0.394)	-2.595*** (0.396)
N	442464	442464	19393	19208
Pseudo R^2	0.060	0.070	0.197	0.166
Log Likelihood	-283813.3	-263783.8	-10585.3	-10090.5
χ^2	35925.2	39590.1	5188.3	4013.2
P-value	0	0	0	0

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.12: Logit Regression of Team Entrepreneurship.

	(1)	(2)	(3)	(4)
	Team of Employ- ees from Previous Employer	Team of Founders from Previous Employer	Team of Employ- ees from Previous Employer	Team of Founders from Previous Employer
Female	-0.424*** (0.0664)	-0.398*** (0.0800)	-0.0499 (0.0873)	-0.0105 (0.0988)
Swedish Background	0.227** (0.0847)	0.268* (0.105)	0.0861 (0.117)	0.110 (0.135)
Age	0.0200*** (0.00347)	0.0141*** (0.00420)	0.000157 (0.00454)	-0.00626 (0.00515)
Tenure	0.0361*** (0.00494)	0.0379*** (0.00587)	0.0399*** (0.00652)	0.0371*** (0.00717)
Education ≤ 11 Years	-0.225*** (0.0644)	-0.234** (0.0784)	0.0565 (0.0850)	0.0351 (0.0960)
Education $>12, \leq 15$ Years	0.0461 (0.0732)	0.113 (0.0866)	-0.224* (0.0920)	-0.129 (0.103)
Education >15 Years	-0.147 (0.448)	-0.317 (0.538)	-0.505 (0.487)	-0.583 (0.568)
Individual Effect	0.507*** (0.0293)	0.442*** (0.0353)	0.109** (0.0382)	0.0610 (0.0439)
Firm Effect	0.294*** (0.0212)	0.253*** (0.0260)	0.109*** (0.0245)	0.0532 (0.0292)
Match Effect	0.0888*** (0.0193)	0.0672** (0.0228)	0.0938*** (0.0276)	0.0523 (0.0302)
Constant	-3.552*** (0.397)	-3.331*** (0.434)	-0.565 (0.514)	-0.479 (0.556)
<i>N</i>	19516	19470	5282	5271
Pseudo <i>R</i> ²	0.094	0.084	0.064	0.061
Log Likelihood	-6415.4	-4738.3	-3225.9	-2685.0
χ^2	1335.1	870.0	439.9	350.3
P-value	7.49e-218	1.90e-126	8.35e-46	1.72e-31

Standard errors in parentheses

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.4: Distributions of First Year Gross Investment

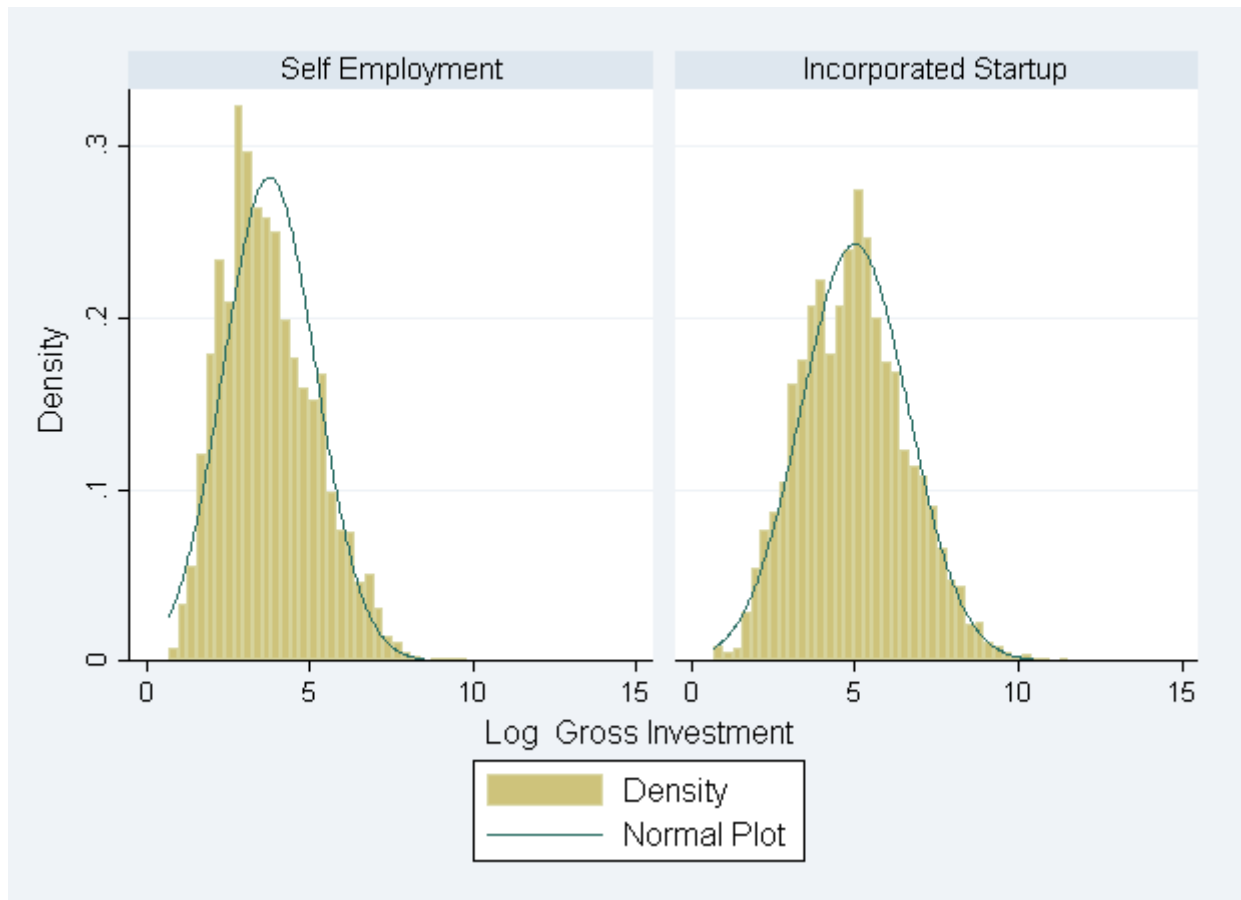


Table 3.13: Summary Statistics of First Year Gross Investment

	Sole Proprietorship				Incorporated Startups			
	mean	sd	min	max	mean	sd	min	max
First Year Gross Investment	140.077	478.017	1.000	15236.000	675.323	3211.473	1.000	104682.000
Observations	4600				2011			

Note: Business investments are in thousand Swedish Kronas.

Table 3.14: OLS Regression of First Year Business Investment of Entrepreneurs

	(1) Log Gross Investment
Incorporated Startup	0.755*** (0.0437)
Female	-0.182*** (0.0422)
Swedish Background	-0.00117 (0.0517)
Age	-0.00689*** (0.00199)
Education ≤ 11 Years	0.0819 (0.0427)
Education $>12, \leq 15$ Years	-0.0710 (0.0476)
Education >15 Years	-0.376 (0.255)
Log Prior Earning	0.0473* (0.0190)
Log Nr. of Employees	0.990*** (0.0448)
Constant	-1.336*** (0.274)
Observations	16522
R^2	0.248

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: All models include 58 industry dummies, 12 year dummies, and 23 municipality dummies.

4 Essay Three: Exploration, Exploitation, and Entrepreneurial Spawning: Evidence from Medical Device Industry

Joint Work with **Corey Phelps (HEC-Paris)**

4.1 Introduction

Spinouts (entrepreneurial firms founded by ex-employees of incumbent firms) are distinctive class of entrants in a variety of industries such as lasers (Klepper and Sleeper, 2005), disk drives (Agarwal et al., 2004), and semiconductors (Gompers et al., 2005). Spinouts seem to perform better than other types of new ventures (Agarwal et al., 2004) and they account for the transfer of knowledge and capabilities (Klepper and Sleeper, 2005) and the evolution of industry clusters (Buenstorf and Klepper, 2009). Entrepreneurial spawning not only differs across industries but also within a single industry firms differ in the rate and intensity of spawning entrepreneurial firms (Gompers et al., 2005). In spite of the recent research on the causes of entrepreneurial spawning there is still little known about what type of firms are more likely to generate spin-outs. In particular existing research suggests that firms with abundant knowledge have higher potential for generating spinouts (Agarwal et al., 2004). Unfortunately this relationship has only been investigated about the quantity and quality of the incumbents' knowledge (Agarwal et al., 2004; Gompers et al., 2005). Little known is how incumbents' knowledge generation strategies by means of exploration and exploitation for new knowledge affect entrepreneurial spawning. In this paper we specifically investigate this relationship by theoretically and empirically linking firms' exploration within the existing knowledge domains and exploration across new knowledge domains to the likelihood and intensity of spin-out generation. Central to our arguments is the interplay between these two types of exploration and firms' complementary assets that determine the entrepreneurial opportunity set that employees can tap on to start their own business.

We integrate organizational learning and innovation literature with entrepreneur-

ship literature to develop theoretical arguments that account for this micro consequence of organizational search behavior, namely the effect of exploration on entrepreneurial departure of employees. We test our theoretical predictions with a sample of publicly traded firms in the medical devices industry from 1985 to 2006.

Our theoretical arguments and empirical analysis contributes to two streams of research. First it adds to the strategy and innovation literature by investigating the micro consequences of organizational learning process above and beyond conventional outcomes such as development of new products, innovativeness, and performance. We argue that the results of learning process (e.g. by exploration and exploitation) might have consequences for organizations' human assets as well. Second we add to the employee entrepreneurship literature by highlighting that the place of employment provides a unique context in which the entrepreneurial behavior of employees are shaped. Recognizing that employee entrepreneurship requires access to opportunities as well as motivation to break apart an otherwise stable employment relationship, we show that the organizational context and in particular the structure of the organization's knowledge base affects both the idle opportunity set and the motivation of employees to spin-out.

The organization of the paper is as follows. First we start with a brief review of the entrepreneurship literature. We proceed to develop our theoretical framework and hypotheses in section three. Next we present our data, sample, and empirical methodology in section four. We then proceed to empirical analysis and present the results. And finally we conclude in the last section.

4.2 Related literature

Entrepreneurship by ex-employees of incumbent firms has been the subject of research in strategy, economics, and organizational sociology. Prior work shows that there is considerable heterogeneity in the rate of spin-out generation among incumbent firms. Some firms never spawn, some generate only a few spin-outs, and some are simply

more fertile than others. A classic example of such a fertile firm in the early days of semiconductor industry is Fairchild with 24 spin-outs among which Intel, National Semiconductor, and Advanced Micro Devices are notable ones (Klepper, 2007; Brittain and Freeman, 1986).

Features of the organization in which employees work has been argued to be associated with their spawning levels. Prior literature identifies organizational features such as bureaucracy (Sørensen, 2007a), size (Sørensen, 2007a; Elfenbein et al., 2010), wage policies (Carnahan et al., 2012), contractual incentives (Anton and Yao, 1995), and innovativeness (Agarwal et al., 2004; Klepper and Sleeper, 2005; Gompers et al., 2005) as notable factors that distinguish firms in their levels of entrepreneurial spawning. In particular, as long as any entrepreneurial activity by individuals requires access to entrepreneurial opportunities and recognition of those opportunities (Venkataraman, 2002), it seems that organizations that are abundant with opportunities and knowledge about the industry provide an environment in which employees may discover, evaluate, and exploit idle opportunities to create valuable future goods and services (Venkataraman, 2002; Agarwal et al., 2004; Klepper and Sleeper, 2005) by means of spinning-out a new and independent firm. Specifically in high-tech industries entrepreneurial opportunities are technical in nature which makes innovative firms as hot beds of entrepreneurial opportunities from which employees spin-out to start their own venture (Gompers et al., 2005; Franco and Filson, 2006). (Agarwal et al., 2004) argue that incumbent firms' investment in new knowledge has the characteristics of public good (Arrow, 1962) that can be appropriated by their employees. In other words employees are well positioned to appropriate their employer's knowledge and transfer it to other organizations including entrepreneurial startups. Incumbent firms are often thought to be imperfect repositories of knowledge where their knowledge can be transferred through movement of their employees in and out of the organization and cause their knowledge to spillover. Therefore knowledge generation by means of innovation at incumbent firms can be seen as an

integral part of entrepreneurial activity by employees, at least in high-tech sectors.

Several researchers have empirically established that innovative firms are more likely to generate spin-outs than non-innovative firms and that innovation is positively associated with the number of entrepreneurial spawns. In studying entrepreneurial spawning in laser industry, Klepper and Sleeper (2005) build a theoretical model where employees learn technical knowledge about a particular product that their employer produces and exploit that knowledge to commercialize a variation of those products in an independent spin-out venture. Klepper and Sleeper argue that greater technical knowledge of incumbent firms increase the pool of market opportunities for spinning-out. They empirically show that intensive patenting of incumbent laser firms is positively associated with the likelihood of spin-out generation. Similar relationship between patenting as a proxy for knowledge and entrepreneurial spawning is shown by Gompers, Lerner, and Scharfstein (2005) in a sample of public firms from a variety of industries. They show that patenting by incumbent firms, particularly in areas attractive for venture capital investors, increases both the likelihood of entrepreneurial spawning and the rate of generating spin-outs. Except for a few recent studies (Agarwal et al., 2004; Ganco, 2013; Andersson et al., 2012), past research looks at entrepreneurial opportunities to be embedded merely in the stock of knowledge of the incumbent firms ignoring the impact of the knowledge generation process and strategies that firms undertake to use their generated knowledge on the motivation of employees to spin-out. Klepper (2007) and Klepper and Thompson (2010) argue that spin-out occurs mainly because of the strategic disagreement between the firm and the employees which drives some employees to resign and found a new venture. The strategic disagreement and subsequently frustration in some employees, especially in high tech sectors, may occur as a result of the firm's active selection and rejection of inventions (Cassiman and Ueda, 2006). In addition, Agarwal et al. (2004) in studying the disk drive industry, argue that although abundance of knowledge might be the indicator of idle opportunities whether employees will act on those opportuni-

ties depends on incumbent's utilization of those opportunities. In other words, if an incumbent firm actively utilizes its technological knowledge in commercial products in the market it may very well deter the utilization of those opportunities by its employees. Literatures on innovation can better inform us about this knowledge generation process and knowledge utilization process. In the next section we relate knowledge generation process by means of exploration and exploitation to entrepreneurial spawning.

4.3 Theory and Hypothesis

Central to our arguments is the interplay between exploration for new knowledge and firms' complementary assets that determine the idle opportunity set for employees to tap on to start their own firm. Below we lay out the foundations for our hypothesis by elaborating on the role of complementary assets, exploration, and the interplay between the two.

4.3.1 Complementary Assets

Originally elaborated by Teece (1986) successful commercialization of an innovation requires that its technological components, which collectively comprise the core know-how of the innovation, be utilized in conjunction with the complementary assets and firm capabilities. When complementary assets are specialized with the core technological know-how of the firm their strategic importance is enhanced since competitors can't readily acquire them through the market (Barney, 1991; Rothaermel and Hill, 2005). For instance successful innovation in pharmaceuticals or medical device industry often requires complementary capabilities in clinical procedures and routines to navigate the FDA's regulatory process. To the extent that firms' capabilities in clinical procedures and routines are specific to a particular therapeutic area, innovations in that therapeutic area become specialized with the firms' complementary assets. Firms' specialized complementary assets are therefore integral for value creation and appropriation from innovations (Gans and Stern, 2003). These complementary assets are hard to imitate

since they result from the process of learning by doing that involves different parts of the organization (Teece, 1992). Shane (2001) also points to the importance of complementary assets for mode of commercialization of inventions, namely through new firm formation or commercialization by incumbents. Shane (2001) finds that availability of specialized complementary assets, such as marketing and distribution, increases the likelihood that an invention is exploited inside an incumbent firm. Similarly, Arora and Ceccagnoli (2006) argue that the ability of firms to appropriate the returns from investment in innovative activity through licensing or internal commercialization depends on the ownership of specialized complementary assets. In particular they find that firms' propensity of out-licensing inventions increases with the lack of specialized complementary assets. Specialized complementary assets are usually built over a long period of time and are often path dependent and idiosyncratic to the technological know-how of the firm (Teece et al., 1997).

As said firms' complementary assets adapt and change over time with technological change and it is the interplay between complementary assets and the characteristics of the new innovations that determine to what extent firm can leverage their existing specialized complementary assets to commercialize new innovations. Technological progress and change often takes place along the dimensions of exploration and exploitation. Following section discusses the role of exploration and exploitation in innovation that together with firm complementary asset predicts the opportunity set available for the firm and employees.

4.3.2 Exploration, Opportunity Set, and Motivation to Spin-out

Apart from its effect on various organizational outcomes, knowledge generation process may impact employees' outcomes as well. After all organizations' human assets, namely employees, are the ones that create new knowledge by combining and recombining various knowledge elements. We argue that an organization's strategy with respect to knowledge

generation and the utilization of that knowledge through complementary assets will alter the idle opportunity set for employees and subsequently entrepreneurial spawning.

March (1991) noted that search for new knowledge takes place along the continuum of exploration and exploitation. According to March, exploration of new knowledge is characterized by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation. Knowledge exploration can be done in a number of ways. When exploring new knowledge firms can rely on their own knowledge assets, cross organizational boundaries Rosenkopf and Nerkar (2001), or combine knowledge from different knowledge domains. Here we distinguish between two types of exploration: *exploration within existing knowledge domains* and *exploration across new knowledge domains*. Our distinction between these two types of exploration activity is for their differential consequence on the firms' idle opportunity set when they are combined with the firms' complementary assets.

Exploration within existing knowledge domains (Exploration scope). A firm's knowledge base is comprised of several knowledge elements belonging to different domains or classes (Yayavaram and Ahuja, 2008). A technological invention can be seen as the outcome of combining these knowledge elements (Fleming, 2001). Exploration within a knowledge domain occur when the firm searches and combines new and old elements of a single knowledge domain. The degree of exploration is determined by the intensity of using new knowledge elements than old knowledge elements to generate a new technological innovation.

Exploration, in general, increases the diversity of the knowledge pool. New knowledge that is generated by means of exploration (as opposed to exploitation) usually exhibits greater uncertainty and the rewards for its further development and commercialization is distant in time. Nevertheless a firm that explores within knowledge domains is likely to build understanding of the knowledge trajectories within those knowledge domains over time. A path dependent nature of knowledge accumulation and generation therefore

means that uncertainties are smaller. In addition a firm that explores within knowledge domains can leverage on the complementary assets that has previously developed for those knowledge domains for commercialization of knowledge. Probably a good example is the FDA regulatory process in pharmaceuticals and medical devices. A firm with past experience in commercializing products in certain therapeutic areas is likely to have built complementary assets with respect to clinical approval procedures and other regulatory process with respect to those therapeutic areas. Thus exploration within knowledge domains pertaining to those therapeutic areas will allow this firm to leverage on the complementary assets in order to commercialize new inventions. The consequence of exploration within knowledge domains on the knowledge pool of the firm is that fewer inventions are likely to be shelved or left idle. This is because the firm can leverage on its specialized complementary assets to further develop or commercialize those inventions. Therefore we are likely to see a diminished idle opportunity set for employees to tap on to start their own business when a firm explores within knowledge domains. Furthermore exploration within knowledge domains may impact the motivation of inventor employees for remaining with the firm. Inventors are usually build expertise in a few knowledge domains however when they are allowed to explore within their knowledge domains they are likely to exhibit less frustration (Hellman, 2007). Therefore we hypothesis:

Hypothesis 1: *Exploration within existing knowledge domains reduces the likelihood and intensity of entrepreneurial spawning.*

Exploration across new knowledge domains (Exploration diversity). Exploration across new knowledge domains occur when the firm searches over new knowledge domains that is unfamiliar with. In other words the firm generates new knowledge by combining knowledge elements that belong to new knowledge classes. Therefore, the degree of exploration across new knowledge domains is the extent to which knowledge elements in a technological innovation belong to new and unfamiliar knowledge classes.

Innovations emanating from exploration across new knowledge domains are even

more uncertain in nature and their rewards are less likely to be reaped in the near future. This basically gives more likelihood of such innovations being rejected by strategic decision makers inside firms (Cassiman and Ueda, 2006). In addition such innovations in order to be developed into commercial products may require new complementary assets and capabilities. The new complementary assets might be related to new distribution networks and marketing channels, as well as new manufacturing capabilities and organizational routines.

Acquiring complementary assets and routines are costly and when combined with the uncertainty inherent in exploratory innovations may deter further development and commercialization of these innovations by incumbent firms. Therefore when a firm explores across new knowledge domains it is likely to increase the size of the idle opportunity set. In other words innovations will be more likely to be shelved than utilized by the firm because of the lack of complementary assets. Arora and Ceccagnoli (2006) show that lack of specialized complementary assets results in more out-licensing of inventions than internal development. When the firm explores across new knowledge domains it is likely to generate innovations that require new complementary assets and capabilities for further development and commercialization. Therefore increase size of the opportunity set means that employees will have access to greater entrepreneurial opportunities.

These innovations are also less likely to be technological in direct competition with the firm's core technologies which further motivates employees to spinout with the technology. Therefore we hypothesize:

Hypothesis 2: *Exploration across new knowledge domains increases the likelihood and intensity of entrepreneurial spawning.*

4.4 Data and Methodology

4.4.1 Data

The context of our study is the U.S. medical device industry. Our sample comprises of all the public medical device firms with headquarters in the U.S. from 1984 to 2006. We briefly describe the data collection process here. The details, however, are available in the appendix. Our main data sources are: COMPUSTAT, Venture Source, and National Bureau of Economic Research's (NBER) patent data files. We used COMPUSTATs segment data to identify public companies in medical device industry. Our sampling strategy includes all the companies whose primary or secondary SIC code in any of their reported segments in any year during our sampling period correspond to one of the medical device sectors¹⁹. It should be noted that this is a broad sampling strategy in a sense that we include a public company in our sample even if it reports a medical device segment only once during the sampling period. This results in 1,090 publicly traded firms that are present during our sampling period at least once. 27 of these firms only have 1 year of observations. We have also used a more restrictive sampling strategy but the results did not change²⁰.

The core information on medical device startups comes from Venture Source²¹. Venture Source was established in 1987 and collects data about firms that have obtained venture capital financing. The data collected include identity and employment background of key executives and board members, as well as the strategy, industry, and financial history of firms. We use the records about the identity and employment background of individuals to identify founders and their prior employer. First, we recorded

¹⁹According to the Office of Health and Consumer Goods following sectors comprise medical device industry: in-vitro diagnostic substances manufacturing (SIC 2835), electro-medical and electrotherapeutic apparatus manufacturing (SIC 3842, 3845), irradiation apparatus manufacturing (SIC 3844, 3845), surgical and medical instrument manufacturing (SIC 3841), surgical appliances and supplies manufacturing (SIC 3821, 3841, 3842, 3851), dental equipment and supplies manufacturing (SIC 3843), ophthalmic goods manufacturing (SIC 3851), dental laboratories (SIC 8072).

²⁰Our most restrictive sampling strategy includes all the companies that consistently report a medical device sector in one of their segments in every year during the sampling period.

²¹Previously Venture One, now a division of Dow Jones.

an individual as a founder if he/she was explicitly identified in Venture Source as a founder/co-founder of the firm or was among the initial executive officers of the firm. We defined initial executive officers as those executives who joined the firm exactly in the same month and year in which the firm was founded. Second we used Capital IQ’s “people intelligence” database to search the founders of startup firms²². Capital IQ’s people intelligence database reports identity of business professionals of both private and public firms and exactly identifies the role of the professionals within the firm including the “founder” or “co-founder” role. We used this piece of information to complement Venture Source. Third, in cases where we could not identify founders in Venture Source and Capital IQ we relied on web searches including searching LinkedIn profiles, company websites, and Factiva.

Consistent with the definition of the “parent firm” in the earlier literature (Phillips, 2002; Agarwal et al., 2004; Klepper, 2007; Sørensen, 2007a) we define a parent firm as the most recent employer of the founders. We used Venture Source and complementary web searches to identify the most recent employer of the founders. We then matched the prior employer of the founders to the sample of public firms compiled from COMPUSTAT²³. Table 1 summarizes the number of entrepreneurs and their VC back spinouts throughout our sampling period. In total there are 549 entrepreneurs emanating from public companies and founding 410 spinout firms from 1984 to 2006 in the medical device industry. To obtain information about spawning firms’ patents and their citations we matched our sample of firms to NBER’s patent data file (Hall et al., 2001)²⁴.

²²People Intelligence covers over 4.5 million professionals and over 2.4 million people including private and public company executives, board members, and investment professionals, globally.

²³Names of prior affiliation of individuals in Venture Source are sometimes misspelled, differently spelled, or abbreviated (e.g. Johnson and Johnson sometimes appear as J&J). Prior to matching with COMPUSTAT we cleaned and standardized the names of parent firms. For matching parent firms with COMPUSTAT we employed a fuzzy matching algorithm based on “*Levenshtein distance*” metric between two strings. The details of the matching procedure are available in the appendix to this paper.

²⁴Available at <https://sites.google.com/site/patentdatapoint/>

4.4.2 Dependent Variables

Spin-out Intensity. We measure the intensity of entrepreneurial spawning with the number of spin-outs that a public firm generates each year. We equate the spawning year with the founding year of the spin-out firms.

Spin-out Generation. This is a dummy dependent variable that takes a value of 1 if a public firm spawns at least one firm in a year. This variable is constructed to investigate the likelihood of entrepreneurial spawning by a public firm in a year.

4.4.3 Independent Variables

Exploration Scope. This variable measures the degree of general knowledge exploration by a public firm in a given year. By general exploration we refer to the theoretical notion of exploration of new knowledge irrespective of the domain of new knowledge. Therefore exploration scope is simply the proportion of new patent citations in a citation list of a firm's patents in a focal year:

$$\text{Exploration Scope}_{it} = \frac{\text{New Patent Citations}_{sit}}{\text{Total Citations}_{it}} \quad (4.1)$$

We adopted a 5 year look back window meaning that new and total citations are searched for the firm's past 5 year patent stock. This way of constructing exploration scope corresponds to a continuum with the range from 0 to 1. Complete exploration is denoted by 1 and complete exploitation is denoted by 0. This is consistent with the theoretical notion of exploration as a continuum (March, 1991; Gupta et al., 2006). It should be noted that when we control for the diversity of exploration in the econometric model, exploration scope effectively captures the degree of exploration within the existing knowledge domains.

Exploration Diversity. This variable measures the degree of exploration across knowledge domains. We characterize knowledge domains by patent classes. When a new

patent in a focal patent class cites another patent belonging to a different patent class it crosses knowledge domains characterizing the diversity of exploration. It should be noted that a cited patent in the same knowledge class as the citing would not contribute to exploration diversity even if it is completely a new knowledge in the citing patent's reference list. We measure exploration diversity with the following formula:

$$\text{Exploration Diversity}_{it} = \frac{\text{New Patent Classes in Patent Citations}_{it}}{\text{Total Patent Classes in Patent Citations}_{it}} \quad (4.2)$$

Similarly we adopted a 5 year look back window to search for new and total patent classes. Exploration diversity also ranges from 0 to 1 with the value of 1 denoting completely diversified exploration (all the knowledge domains used are new to the firm compared to the firm's last 5 years of knowledge classes) and 0 denoting complete exploitation of the firm's existing knowledge domains.

4.4.4 Control Variables

We control for firm *size* for the following reasons. Prior research shows that small firms are more likely to spawn entrepreneurs than large firms (Sørensen, 2007; Elfenbein, Hamilton, & Zenger, 2010). To the extent that firm size is also associated with exploration behavior of firms, this would create a spurious relationship between organizational exploration and entrepreneurial spawning. Past research provides mixed evidence of the effect of firm size on the antecedents of exploration and exploitation. The level of exploitation may increase with firm size (Cohen and Klepper, 1996; Rothaermel and Hill, 2005) because of the increasing returns for incremental improvements on existing knowledge. On the contrary firm size may imply greater resources to devote to exploration as well (Beckman et al., 2004; Greve, 2007). We use annual sales as a proxy for firm size. We obtain annual sales data from COMPUSTAT.

We also control for firm *age*. Klepper and Sleeper (2005) show that entrepreneurial

spawning has a nonlinear relationship with age having its peak when firms are in their middle age. Firm age may also be correlated with exploration behavior of firms. As firms age they become more bureaucratic and may build more structure and inertia on their strategic orientation regarding knowledge exploration (Kelly and Amburgey, 1991; Lavie and Rosenkopf, 2006). We measure firm age with the years since listing of the company with the Securities and Exchange Commission (SEC). This is an economically meaningful measure of firm age (Shumway, 2001) and it is calculated similarly in earlier research (Fama and French, 2004). We obtain the first date of companies' listing with SEC from Center for Research in Securities Prices (CRSP).

Past research suggests that firm exit (e.g. through dissolution or mergers and acquisitions) might trigger the departure of employees to entrepreneurship. When firms fail through dissolution their knowledge does not fade away (Hoetker and Agarwal, 2007). In fact employees of the failed firms may use this knowledge to their advantage by forming new firms. Second, vital events such as mergers and acquisitions may cause the acquired firm to undergo significant changes in its incentive systems, levels of bureaucratization, and corporate culture. Earlier research suggests that changes due to mergers and acquisitions not only induces significant turnover of employees (Walsh, 1989; Hambrick and Cannella, 1993) but may also trigger founding of new firms by the employees of acquired firms (Stuart and Sorenson, 2003). We therefore control for *firm exit* by creating a dummy variable that takes a value of 1 if the observation year is the last year that a firm is observed in our sample and 0 otherwise. We remain ignorant of the cause of exit.

One of the consistent determinants of entrepreneurial spawning is the firms' stock of knowledge. Firms are repositories of knowledge and abundance of this knowledge may bestow unique and idiosyncratic information about entrepreneurial opportunities to employees (Agarwal et al., 2004). Earlier research using patent data as a proxy for firm knowledge shows that firms with greater stock of patents are more likely to spawn entrepreneurial ventures (Agarwal et al., 2004; Klepper and Sleeper, 2005; Gompers

et al., 2005; Franco and Filson, 2006). Therefore we control for the firms' stock of knowledge with their *patent stock* over the past 5 years. We also control for the firms *patent quality* as described in Jaffe and Trajtenberg (2002). As elaborated in Jaffe and Trajtenberg (2002) a measure of patent quality is the number of forward citations that a patent receives. We aggregate this measure to the firm level and define a firm's patent quality in a given focal year as the total number of forward citations that a firm receives for its risk set of patents in that focal year. A firm's citation risk set contains all the firm's patents whose application year is within a defined time window. We adopt a five year risk set that contains all the firm's patents whose application year is within the past five year window of the current focal year. The size of the risk set is therefore equivalent to the firms' patent stock as defined above.

The degree to which a firm explores for new knowledge or combines knowledge from different domains may be directly related to the diversity of its lines of business. Exploration within and across knowledge domains might be the manifestation of a firm's diversification along different product markets and lines of business (Lavie et al., 2010). Entrepreneurial ideas in diversified firm may also find fit within the firm's multiple product markets, hence inhibiting the departure of employees to spin-outs. Gomper, Lerner, and Schafstein (2005) provide support for this argument by showing that focused firms, those that are active in only one business segment, are more likely to generate spin-outs. We therefore control for the possible confounding effect of diversification on entrepreneurial spawning with the *number of business segments* that a firm operates in each year. We count the yearly number of business segments that a firm reports in COMPUSTAT to measure the degree of diversification along business lines.

Technologically divers firms may be more innovative in general (Garcia-Vega, 2006) and they may be able to engage in technological exploration by cross fertilizing knowledge from diverse domains and move beyond local search (Quintana-García and Benavides-Velasco, 2008; Phelps, 2010). We measure technological diversity of firm i in year t

according to a modified Herfindahl index (Hall, 2002):

$$\text{Technological Diversity}_{it} = [1 - \sum_{j=1}^J (\frac{N_{jit}}{N_{it}})^2] \times \frac{N_{it}}{N_{it} - 1} \quad (4.3)$$

where N_{it} is the number of patents obtained by firm i in the past five years. N_{jit} is the number of patents in technology class j in firm i 's five year patent stock.

We also control for the possible endogeneity arising from the state level differences in the enforcement of non-compete covenants. Earlier research shows that strict legal support for non-compete covenants greatly impedes the mobility of employees across organizations (Marx et al., 2009) as well as entrepreneurship in those geographical regions (Stuart and Sorenson, 2003; Samila and Sorenson, 2011). Garmaise (2011) creates a non-compete enforcement index for each U.S. states based on Malsberger's (2004) survey of jurisdictions on the enforceability of non-compete laws during 1992-2004. Although Garmaise (2011) reports these indices for the period 1992-2004, state laws regarding non-compete covenants remained relatively stable for the periods before 1992 and after 2004. As noted by Samila and Sorenson (2011) most states had relatively stable enforcement regimes for the past 30 years²⁵. Therefore we use the same indices developed by Garmaise (2011) from 1985 to 2006 to characterize the enforcement of non-compete laws in the headquarter state of the firms in our sample. These indices are available in the appendix.

Finally in our model specifications we control for the possible industry trends in the medical device industry with a full set of year dummies. Including year dummies should control for the effects of industry evolution and competitive density on entrepreneurial spawning (Brittain and Freeman, 1986).

²⁵Michigan inadvertently experienced a change on its legislations in 1985 which made non-compete agreements unenforceable. 1985 is the start of our panel so this change should have very little effect on the results. Florida slightly strengthened its enforcement in 1996, and Louisiana made non-compete covenants unenforceable from 2002 to 2004 (Garmaise, 2011). We incorporate these changes in the indices.

4.5 Analysis and Results

We use two statistical specifications for our analysis. We use logistic regression to test the likelihood of entrepreneurial spawning and negative binomial regression to test the intensity of entrepreneurial spawning.

We use a random-effects logistic regression with the following specification:

$$P_{it} = F(\beta X_{it} + \gamma Z_i + \tau_t + u_i) = F(Y_{it}) = \frac{e^{Y_{it}}}{(1 + e^{Y_{it}})} \quad (4.4)$$

where P_{it} is the probability that firm i generates at least one spin-out in year t . X_{it} is the vector of time varying firm characteristics including both independent and control variables, Z_i is the time invariant vector that only includes the non-compete enforcement index of state in which the headquarter of firm i is located, and τ_t is a full vector of time dummies. Random effects are shown by u_i . Our choice of random effects model was for the following reasons. Multiple observations of each firm over several years raise the concern of potential interdependence of the error structure among firm-year observations of the same firms. More importantly random effects specification allows for across group variance which is the main objective of this paper. To investigate the intensity of entrepreneurial spawning (the number of spin-outs a firm generates) we use the random effects negative binomial regression. This is because our dependent variable, spin-out intensity, is a count variable.

Table 4.1 shows the descriptive statistics and correlations of all the variables in our study. Examination of the bivariate correlations reveals that multicollinearity is not a major issue. We also computed variance inflation factors (VIF) for all the variables. All the variables have VIFs less than 3 which are below the suggested threshold of 10 for severe collinearity.

The results of the random effects logistic regression are presented in table 4.3. Model 1 only includes control variables. Similar to the findings of past research a firms stock

patents positively affects the likelihood of spinout generation. This is consistent with the idea that the abundance of technological knowledge enables access and recognition of entrepreneurial opportunities. The coefficient of non-compete enforcement index is negative and significant. This is also consistent with the general findings of the effect of non-compete covenants on labor mobility and entrepreneurship. Model 2 introduces exploration scope. As hypothesized the coefficient of exploration scope is negative and significant at conventional levels. The odds ratio of exploration scope is about 0.47 which in terms of percentage change means that a one unit increase in a firm's exploration scope reduces the odds of spin-out generation by 53%. Model 3 only introduces exploration diversity along with the full set of control variables. The coefficient of exploration diversity is positive and highly significant. Its odds ratio is 2.72 which in terms of percentage change imply a 172% increase in the odds of spin-out generation with one unit increase in a firm's exploration diversity. Model 4 is the full model where we include both exploration scope and diversity along with the full set of control variables. Exploration scope is again negative and highly significant. Controlling for exploration diversity slightly increases the effect of exploration scope. It should be noted that controlling for exploration diversity isolates the theoretical interpretation of exploration scope. When controlling for the diversity of exploration, exploration scope refers to the firms' within domain knowledge exploration. The odds ratio of exploration scope is now 0.42 which in terms of percentage change imply a 58% reduction in the odds of spin-out generation with one unit increase in the firm's exploration scope. The coefficient of exploration diversity remains positive and highly significant as well. Its odds ratio is about 3 which in terms of percentage changes imply a 200% increase in the odds of spinout generation with a unit increase in the firm's diversity of exploration.

Table 4.4 reports the results of the random effects negative binomial regression in which the dependent variable is the count of spinouts that firms generate each year. Model 1 only includes our control variables. Similar to the findings of past literature a

firm's amount of technological knowhow significantly affects the number of spinouts that a firm generates. The coefficient of non-compete covenants is no longer significant although as anticipated its direction is negative. This means that stronger enforcement of non-compete covenants has no meaningful impact on the intensity (number) of generating spin-outs. Models 2 to 4 add our independent variables to the regressions. In our full model (model 4) the coefficient of exploration scope is negative and significant at 0.05% level (P-value = 0.028). Exploration scope therefore significantly reduces the intensity of spin-out generation. The coefficient of exploration diversity is positive and significant at 0.05% level (P-value = 0.037) implying that the intensity of entrepreneurial spawning significantly increases with the increases in diversity of exploration. In other words firms that explore along more diverse knowledge domains spawn more entrepreneurial ventures than firms that explore along fewer knowledge domains.

4.6 Robustness Checks

To ensure the robustness of our results we performed several alternative checks. First we extended the look back window to 7 years and computed all the measures including the measures of exploration scope and exploration diversity over the 7 year look back window. The results of our analysis did not affected by extending the look back window. Second as mentioned earlier our analysis sample covers a broad range of firms in medical device industry in a sense that we include a public company in our sample even if it reports a medical device segment only once during the sampling period. To the extent that medical device sector does not encompass the core line of business of a company this may bias our results since observing a venture capital backed spin-out becomes unlikely for firms that are not active in the medical device sector. Although controlling for diversity in a firm's businesses may partly reduce the bias, to ensure that our results are not driven by our broad sampling strategy we performed the analysis once again with a more restrictive sample of firms. Our most restrictive sampling strategy includes all

the companies that consistently report a medical device sector in one of their segments in every year during the sampling period. This reduces the number of firms to 881 firms that were consistently active in the medical device sector either during entire life. The results of our analysis were robust to the restricted sample as well.

A potential concern in our analysis is endogeneity where an unobserved firm characteristic is correlated with both the exploration scope and exploration diversity as well as firm's propensity to generate spin-offs. To alleviate concerns about endogeneity I repeat the regressions with firm fixed effects. Essentially firm fixed effects should absorb any stable and unobserved firm characteristics that would bias the estimates of exploration scope and diversity if they are omitted from the regression specification. Table 4.5 reports the results of the conditional fixed effects logistic regression. The coefficients of both exploration scope and diversity have the similar direction to the random effects model, however only exploration diversity is statistically significant at 10% level. Table 4.6 reports the results of the conditional fixed effects negative binomial regression. Only exploration diversity has the positive sign and is statistically significant at 10% level. One reason that the results are partially supported in the fixed effects specification is that the fixed effects specification is a very strong specification that absorbs the variation of independent variables. Exploration scope and diversity are likely to be associate with the long term firm strategy for those activities and therefore their variation might be absorbed in the fixed effects specification. The other reason is that using fixed effects reduces the number of observations dramatically. Essentially reduction of the number of observations reduces statistical power necessary to detect any effect. The reduction in sample size is because the conditional fixed effects specification only uses firm observations in which the firm spawns at least one spin-out during the sample interval.

4.7 Discussion and Conclusion

Organizations innovate by combining and recombining existing pieces of knowledge. This process of combination and recombination is usually preceded by search (exploration) for knowledge within and across various knowledge domains. It is well established that various organizational outcomes such as innovativeness, new product introduction, and performance hinges on the organizations' capacity to explore. What is less known is the effect of exploration on the outcomes of organizations' human assets. Our paper started by observing this gap.

We integrated organizational learning and innovation literature with entrepreneurship literature to develop a theoretical framework that accounts for micro consequences of organizational search process on entrepreneurial departure of organizations' human assets. Central to our arguments was the interplay between knowledge generation and utilization with organizations' complementary assets. Complementary assets determine whether an organization can reap the rewards from its innovative activity. In particular when the complementary assets are aligned with the core technology of the organization, the organizations can effectively use and commercialize its invention. Core technologies usually emerge in a path dependence manner when organizations explore for new knowledge. Organizations' existing knowledge domains determine the extent of their complementary assets in those domains. When an organization explores within its existing knowledge domains generates inventions that are aligned with its complementary assets. On the other hand, exploring knowledge domains that are new to the firm bears the risk that the outcomes of inventive activity be unaligned with the complementary assets required for effective commercialization. Implications for the idle opportunity is that new knowledge generated by means of exploration within existing knowledge domains is less likely remain underutilized whereas new knowledge generated by means of exploration across knowledge domains is more likely to remain underutilized. Employees therefore may be able to tap on the idle opportunity set to start their own business.

We test our theoretical model with a sample of publicly traded firms in the medical devices industry from 1985 to 2006. Testing our hypothesis using both logistics regression and negative binomial regression we find strong support for the hypotheses that greater search scope (e.g. greater exploration) reduces both the likelihood and the intensity of spin-out generation by employees. We argue that such negative effect of exploration within existing knowledge domains (exploration scope) on employee entrepreneurship is probably because of the diminished size of the idle opportunity set since the firm is better positioned to commercialize innovations with the help of its complementary assets.

We also find positive effect of exploration across knowledge domains (exploration diversity) on employee entrepreneurship. This implies that opportunities that emerge from integrating different classes of knowledge are more suitable for spinning out. Exploration across knowledge domains create inventions that are less likely to fit with the organization's complementary assets. It might be also that due to high uncertainty of the potential of opportunities emerging from higher exploration diversity and the possibility that further development of these opportunities may create integrative challenges for the organization, they might be more likely to be rejected from further development by the organization. Rejection of opportunities from further development may therefore increase the idle opportunity set for employees to tap on to found their own entrepreneurial firms.

In sum our research contributes to both the strategy and innovation, and entrepreneurship literature by integrating the insights from organizational learning literature and that of the entrepreneurship literature. We show that the consequences of organizational learning processes goes above and beyond conventional outcomes such as development of new products, innovativeness, and performance of the firm, and may have micro consequences on the organizations' human assets as well.

Table 4.1: Descriptive Statistics

	mean	sd	min	max
Spin-outs	.0361763	.2131195	0	4
Spin-out generation	.0321035	.1762961	0	1
Exploration Scope (5 Year Window)	.6534762	.3173424	0	1
Exploration Diversity (5 Year Window)	.154014	.2176412	0	.8888889
Technological Diversity	.4750694	.3361761	0	.9848643
5 Year Patent Stock	191.6517	674.6955	0	8604
EBITDA / Assets	-.0888795	.7438763	-30.13084	.9412581
Sales (Proxy for Size)	2.128982	8.900277	0	160.854
Firm Age	17.51557	16.79012	1	82
Nr. of Business Segments	1.861284	1.454698	1	11
Firm Exit	.0213225	.1444743	0	1
Non-Compete Enforcement Index	4.609727	2.309258	1	10
Observations	4174			

Table 4.2: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12
(1) Spin-outs	1											
(2) Spin-out generation	0.932***	1										
(3) Exploration Scope (5 Year Window)	-0.0740***	-0.0742***	1									
(4) Exploration Diversity (5 Year Window)	0.0184	0.0221	0.0612***	1								
(5) Technological Diversity	0.0902***	0.0885***	-0.202***	0.180***	1							
(6) 5 Year Patent Stock	0.130***	0.127***	-0.0945***	-0.0406**	0.347***	1						
(7) EBITDA / Assets	0.0303	0.0294	0.0215	0.0926***	0.219***	0.0883***	1					
(8) Sales (Proxy for Size)	0.124***	0.132***	-0.104***	-0.0419**	0.282***	0.750***	0.0797***	1				
(9) Firm Age	0.0814***	0.0780***	-0.113***	0.0352*	0.561***	0.536***	0.220***	0.515***	1			
(10) Nr. of Business Segments	0.0510***	0.0585***	-0.0732***	0.0339*	0.441***	0.490***	0.159***	0.526***	0.615***	1		
(11) Firm Exit	0.0139	0.0108	-0.0544***	-0.0234	0.000949	-0.0278	-0.00237	-0.0260	-0.0209	-0.00759	1	
(12) Non-Compete Enforcement Index	-0.0185	-0.0304*	0.0517***	0.0301	0.107***	-0.0144	0.0542***	0.00547	0.139***	0.104***	-0.0339*	1
Observations	4174											

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Variables Exploration Scope, Exploration Diversity, Technological Diversity, and Patent Stock are computed over the 5 year lookback window.

Table 4.3: Random Effects Logit Regression of Spin-out Generation

	DV: Spin-out generation			
	(1)	(2)	(3)	(4)
Exploration Scope (5 Year Window)		-0.670 ⁺ (0.386)		-0.787* (0.397)
Exploration Diversity (5 Year Window)			0.964 ⁺ (0.504)	1.094* (0.509)
5 Year Patent Stock	0.000317 (0.000175)	0.000314 (0.000173)	0.000343 (0.000176)	0.000342 (0.000174)
Technological Diversity	1.261* (0.491)	1.100* (0.499)	1.183* (0.496)	0.999* (0.503)
EBITDA / Assets	0.304 (0.344)	0.369 (0.355)	0.275 (0.344)	0.353 (0.357)
Sales (Proxy for Size)	0.00583 (0.0109)	0.00639 (0.0108)	0.00532 (0.0110)	0.00596 (0.0109)
Firm Age	-0.00587 (0.0112)	-0.00531 (0.0111)	-0.00510 (0.0112)	-0.00445 (0.0111)
Nr. of Business Segments	-0.00964 (0.0971)	-0.0110 (0.0964)	-0.0147 (0.0976)	-0.0169 (0.0968)
Firm Exit	0.715 (0.596)	0.658 (0.596)	0.777 (0.598)	0.720 (0.597)
Non-Compete Enforcement Index	-0.140* (0.0616)	-0.136* (0.0610)	-0.141* (0.0621)	-0.136* (0.0615)
Observations	4174	4174	4174	4174
Log Likelihood	-500.0	-498.5	-498.2	-496.3
χ^2	57.83	60.71	60.10	63.34
P-value	0.00167	0.00111	0.00131	0.000791

Standard errors in parentheses

Note: All models include year fixed effects. The dependent variable “Spin-out Generation” takes a value of 1 if a firm generates at least one spin-out in the year and 0 otherwise.

⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4: Random Effects Negative Binomial Regression

	DV: Spin-out Intensity			
	(1)	(2)	(3)	(4)
Exploration Scope (5 Year Window)		-0.625 ⁺ (0.351)		-0.731* (0.361)
Exploration Diversity (5 Year Window)			0.845 ⁺ (0.465)	0.974* (0.470)
5 Year Patent Stock	0.000300 (0.000159)	0.000295 (0.000156)	0.000319* (0.000160)	0.000316* (0.000156)
Technological Diversity	1.201** (0.454)	1.049* (0.462)	1.130* (0.457)	0.954* (0.465)
EBITDA / Assets	0.252 (0.315)	0.311 (0.326)	0.226 (0.314)	0.296 (0.327)
Sales (Proxy for Size)	0.000161 (0.00946)	0.000684 (0.00941)	-0.000207 (0.00946)	0.000393 (0.00940)
Firm Age	0.00324 (0.00989)	0.00400 (0.00984)	0.00389 (0.00992)	0.00478 (0.00985)
Nr. of Business Segments	-0.0603 (0.0854)	-0.0616 (0.0846)	-0.0645 (0.0856)	-0.0666 (0.0847)
Firm Exit	0.812 (0.507)	0.758 (0.508)	0.868 (0.508)	0.817 (0.507)
Non-Compete Enforcement Index	-0.0847 (0.0565)	-0.0845 (0.0560)	-0.0826 (0.0571)	-0.0823 (0.0565)
Observations	4174	4174	4174	4174
Log Likelihood	-547.6	-546.1	-546.0	-544.0
χ^2	60.60	63.84	63.44	67.18
P-value	0.000778	0.000465	0.000521	0.000269

Standard errors in parentheses

Note: All models include year fixed effects. The dependent variable “Spin-out Intensity” is a continuous variable that counts the number of spin-outs a firm generates in each year.

⁺ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.5: Fixed Effects Logit Regression of Spin-out Generation

	DV: Spin-out Generation			
	(1)	(2)	(3)	(4)
Exploration Scope (5 Year Window)		0.0711 (0.489)		-0.0266 (0.499)
Exploration Diversity (5 Year Window)			1.059 + (0.573)	1.063 + (0.578)
5 Year Patent Stock	0.000107 (0.000214)	0.000108 (0.000214)	0.000124 (0.000214)	0.000123 (0.000214)
Technological Diversity	-0.319 (0.769)	-0.303 (0.777)	-0.291 (0.776)	-0.296 (0.782)
EBITDA / Assets	0.538 (0.615)	0.538 (0.614)	0.591 (0.629)	0.591 (0.629)
Sales (Proxy for Size)	-0.00942 (0.0130)	-0.00949 (0.0130)	-0.00973 (0.0130)	-0.00971 (0.0130)
Firm Age [1 – 4]	0.800 (1.368)	0.787 (1.371)	0.646 (1.372)	0.651 (1.375)
Firm Age [5 – 7]	0.900 (1.254)	0.893 (1.255)	0.791 (1.257)	0.794 (1.258)
Firm Age [8 – 12]	0.419 (1.140)	0.407 (1.143)	0.318 (1.142)	0.323 (1.145)
Firm Age [13 – 19]	0.00745 (0.888)	-0.00154 (0.891)	-0.0700 (0.888)	-0.0668 (0.890)
Firm Age [20 – 30]	-0.302 (0.593)	-0.303 (0.593)	-0.363 (0.595)	-0.363 (0.595)
Nr. of Business Segments	0.0616 (0.120)	0.0615 (0.120)	0.0593 (0.120)	0.0594 (0.120)
Observations	897	897	897	897
Pseudo R^2	0.090	0.091	0.097	0.097
Log Likelihood	-240.3	-240.3	-238.7	-238.7
χ^2	47.82	47.84	51.19	51.19
P-value	0.0358	0.0458	0.0226	0.0295

Standard errors in parentheses

Note: All models include year fixed effects. The dependent variable “Spin-out Generation” takes a value of 1 if a firm generates at least one spin-out in the year and 0 otherwise. The omitted firm age group is [20 – 30]. The firm age groups are created in such a way that each group contains roughly the same number of observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.6: Fixed Effects Negative Binomial Regression of Spin-out Intensity

	DV: Spin-out Intensity			
	(1)	(2)	(3)	(4)
Exploration Scope (5 Year Window)		0.135 (0.458)		0.0373 (0.466)
Exploration Diversity (5 Year Window)			0.985 + (0.535)	0.980 + (0.540)
5 Year Patent Stock	0.000178 (0.000178)	0.000179 (0.000179)	0.000187 (0.000179)	0.000187 (0.000179)
Technological Diversity	-0.418 (0.727)	-0.389 (0.735)	-0.375 (0.733)	-0.368 (0.738)
EBITDA / Assets	0.523 (0.560)	0.524 (0.559)	0.565 (0.570)	0.565 (0.570)
Sales (Proxy for Size)	-0.0109 (0.0116)	-0.0111 (0.0116)	-0.0110 (0.0116)	-0.0110 (0.0116)
Firm Age [1 – 4]	0.699 (1.164)	0.682 (1.165)	0.536 (1.171)	0.530 (1.173)
Firm Age [5 – 7]	0.807 (1.069)	0.804 (1.069)	0.708 (1.075)	0.705 (1.075)
Firm Age [8 – 12]	0.284 (0.984)	0.269 (0.986)	0.192 (0.989)	0.187 (0.991)
Firm Age [13 – 19]	0.272 (0.749)	0.259 (0.751)	0.195 (0.751)	0.191 (0.752)
Firm Age [20 – 30]	-0.00466 (0.466)	-0.00552 (0.466)	-0.0680 (0.470)	-0.0683 (0.470)
Nr. of Business Segments	0.00756 (0.0988)	0.00744 (0.0988)	0.00852 (0.0988)	0.00850 (0.0988)
Observations	897	897	897	897
Log Likelihood	-276.6	-276.5	-274.9	-274.9
χ^2	38.04	38.16	40.84	40.87
P-value	0.214	0.246	0.164	0.194

Standard errors in parentheses

Note: All models include year fixed effects. The dependent variable “Spin-out Intensity” is a continuous variable that counts the number of spin-outs a firm generates in each year. The omitted firm age group is [20 – 30]. The firm age groups are created in such a way that each group contains roughly the same number of observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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A Literature Review

In this section I briefly review the research on new firm formation by ex-employees of incumbent firms. This section will elaborate on the causes and consequences of spin-off formation by ex-employees of incumbent firms and review the empirical findings across different contexts and levels of analysis.

A.1 Antecedents of Employee Entrepreneurship

Antecedents of employee entrepreneurship refer to the underlying reasons behind employees' voluntary breaking up of employment relationship with incumbent firms to start entrepreneurial ventures. In other words the aim is to answer the following question: why employees of incumbent firms often leave to become entrepreneurs? A follow up question naturally arises from the first one: why some firms spin-out more entrepreneurial ventures than other firms? Here I explore both the theoretical and empirical works.

Theoretical works:

Appropriation of incumbent firm's knowledge (opportunity recognition).

The first stream of theoretical works on employee entrepreneurship relates to the positional advantages that are accrued to employees of incumbent firms than other individuals. One of the fundamental purposes of organizations is generation and exploitation of knowledge (Kogut and Zander, 1992). In fact, competitive advantage of organizations hinges on constant generation and exploitation of new knowledge (Barney, 1991; Grant, 1996). Organizations typically generate new knowledge by enabling individually held knowledge of employees to be shared and transferred among the members of the organization. Agarwal et al. (2004) argue that incumbent firms' investment in new knowledge has the characteristics of public good (Arrow, 1962) that can be appropriated by their employees. In other words employees are well positioned to appropriate their employer's knowledge and transfer it to other organizations including entrepreneurial startups. Incumbent firms are often thought to be imperfect repositories of knowledge where their

knowledge can be transferred through movement of their employees in and out of the organization and cause their knowledge to spillover.

Given that incumbent firms are the sources of valuable knowledge about new technological knowhow or market related opportunities, we still need to understand why incumbent knowledge should be related to entrepreneurship by their employees. Several researchers (Agarwal et al., 2004; Gompers et al., 2005; Klepper and Sleeper, 2005) have argued that firms with abundant knowledge are the sources of spin-out generation mainly because of increased recognition of opportunities. Incumbent firms' knowledge base may contain valuable, unique, and idiosyncratic information about opportunities in an industry. Although incumbent firms cannot perfectly safe guard against spillover of their knowledge to the outside environment, firm boundaries to a large extent create information asymmetry between employees of the firm and individuals outside organization. Employees privileged access to valuable knowledge may serve as source of advantage (Venkataraman, 2002) in recognizing entrepreneurial opportunities ahead of other individuals in the industry. Since in this way knowledge is equated with opportunities, existing literature (Agarwal et al., 2004; Gompers et al., 2005; Klepper and Sleeper, 2005; Franco and Filson, 2006) equate greater knowledge with greater opportunities. Therefore these researchers propose that the greater the knowledge of an incumbent firm is the greater is its likelihood of spin-out generation. As Agarwal et al. (2004) argues a firm's knowledge can be related to both technological knowhow and market related knowhow and abundance of knowledge in either dimension may reflect opportunities in technical domain or market pioneering domain. Nevertheless, Agarwal et al. (2004) also argue that although abundance of knowledge might be the indicator of idle opportunities whether employees will act on those opportunities depends on incumbent firms' utilization of those opportunities. In other words, if an incumbent firm actively utilizes its technological knowledge in commercial products in the market it may very well deter the utilization of those opportunities by its employees. Agarwal et al. (2004, p. 504)

notes that “When an organization’s strategy emphasizes either technological know-how or market pioneering know-how, identified but unexploited opportunities result”. New scientific breakthroughs that are not commercialized and marketing insights into emerging and unfulfilled customer needs that are not met with technological breakthroughs are both symptomatic of underexploited know-how.

There are several reasons for why such under-exploitation of knowledge by incumbent firms may result in entrepreneurship by employees. First, the likelihood of frustration among employees is likely to be heightened when organizations do not pursue opportunities that they create (Garvin, 1983; Christensen, 1993; Agarwal et al., 2004; Klepper and Sleeper, 2005). Especially in high-tech industries employees who invent new technologies may also develop emotional attachment to their technological inventions and the rejection of their inventions from commercialization by the incumbent may therefore trigger frustration and a sense that the employer is missing out on value appropriation opportunities. A career aspirational gap might be developed between employees and the employer if the employer systematical misses on valuable opportunities and may lower occupational satisfaction among employees. One reason for occupational satisfaction in employees is the sense of recognition of their efforts by their employers. Employers who miss to recognize their employees’ efforts may lower satisfaction among employees and probably trigger entrepreneurial behavior among some employees. Second, under-exploitation of knowledge by incumbent firms might be very well emerging from the fear of cannibalization of incumbent firms’ existing technologies (Klepper and Sleeper, 2005). Such fear of cannibalization in incumbents may in turn increase the confidence in employees that by pursuing entrepreneurial opportunities they will receive less competitive pressure and litigation possibilities from their previous employers and their ventures may survive longer as well.

Incentives, contractual arrangements, and Policies (motivation, policies toward fit). Apart from knowledge of the incumbent firms as sources of entrepreneurial

opportunities, other researchers focus on alternative mechanisms to seek the answer to why employees become entrepreneurs? At one side there are literatures that investigate firm policies and incentives in managing employees' innovative efforts (Anton and Yao, 1995; Pakes and Nitzan, 1982; Cassiman and Ueda, 2006; Hellmann, 2007). Anton and Yao (1995) start with a situation where an employee has a valuable invention and faces a dilemma of revealing it to her employer for internal development or developing her invention in a spin-out firm. Anton and Yao (1995) examine the incentives faced by an employer and employee after the employee privately discovers a significant invention. The feature of their model is that a business start-up by an employee is an inefficient outcome of an information asymmetry between the employer and the employee and the expropriation potential of the invention by the employer. In their model the employee has three strategic options: First she can decide not to reveal the invention to her employer and use it in a start-up. This depends on the rents that she can obtain from the invention through the start-up given that the firm's R and D department can also come up with that invention with some probability and therefore reduce the employee's monopoly rents from the invention to duopoly rents. Second, the employee can reveal the invention to the firm and risk expropriation. By revealing the invention, the employee solves the information asymmetry problem and has the possibility of an ex-post contract offer from the firm but risks expropriation of the invention as well. The firm can use the invention without paying anything to the employee (in this case employee may start-up and drive the firm's monopoly profits down to duopoly profits) or the firm can offer the employee enough incentives to preserve its monopoly use of invention. In the third case, the employee may decide not to reveal the invention to the firm and seek an ex-ante contract from the firm and delays revealing the discovery until contractual incentives are established. The firm's acceptance of ex-ante contract depends on the employee wealth which she puts as a bond that is forfeited if the invention cannot bring up monopoly profits.

Hellmann (2007) build a formal theoretical model where employees face a multitask problem of focusing on their core activities dictated by their employer or explore new ideas with potentially higher private benefits through entrepreneurship. The employee's exploration and exploitation trade-off depends on the firm's policies to keep the focus of employees on their core tasks (discourage them from innovation) or allow incentives for exploration in which some of the ideas of employees are implemented as intrapreneurial projects and some as entrepreneurship in an external venture. In other words, Hellmann suggests that entrepreneurship by employees depends on the extent to which the firm wants innovations that fit with its core activities or innovations that may fall outside of the core activities of the firm and may generate private benefits for employees. Hellmann's (2007) model suggests a systematic rejection of employees' innovations that do not fit with the core activities of the firm. A closely related model to Hellmann (2007) which takes dynamic lens of project rejection is suggested by Cassiman and Ueda (2006). The model by Cassiman and Ueda assumes that the firm has a limited capacity for internal venturing and the firm trades-off the returns of an employee's innovation against the option value of waiting for better innovations in the future. Their model generates optimal project rejection equilibrium where the firm does not look at innovations of its employees in isolation but considers a dynamic optimization process. In Cassiman and Ueda's paper, employees leave to become entrepreneurs when commercialization of their inventions is rejected. Cassiman and Ueda's model project rejection depending on the characteristics of innovations namely their degree of fit with the firm's internal resources, their degree of cannibalization of existing revenue streams, and the degree of profitability of innovations.

As Cassiman and Ueda noted in their model, cannibalization of firms' existing products, capabilities, and hence revenue streams is one reason that sometimes incumbent firms intentionally miss some opportunities. Klepper and Sleeper (2005) also incorporate cannibalization likelihood in the firm's decision to commercialize different variations

of their existing products. In Klepper and Sleeper's Hotelling like model, cannibalization occurs because the new variant of an incumbent firm's product occupies some of the product market space of the firm's existing products and thereby reduces the revenue streams from the firm's existing products. A spin-out would not have a threat of cannibalization since it does not have any market to cannibalize.

Whether rejection of employees' inventions is because of enforcing fit (Hellmann, 2007) or fear of cannibalization (Pakes and Nitzan, 1983; Hellman, 2007; Cassiman and Ueda, 2006) or low profitability prospects, employees might become frustrated by the rejection of their inventions. Anecdotal evidence regarding frustration of employees and their subsequent departure to start their own business is prevalent in many industries such as automobiles and semiconductors (Klepper and Thompson, 2010). A notable example is Amdahl Computer which was founded by Gene Amdahl after his proposition for a venture was rejected several times by IBM, his employer at the time. Another example which illustrates creation of new ventures as a result of frustration is Fairchild Semiconductors which was founded by eight engineers who left Shockley Semiconductors because of frustration with the managerial style of William Shockley, the founder of Shockley Semiconductors, and his authoritarian policy towards innovation.

One of the most salient incentive systems used in organizations is pay systems. The way that organizations compensate their members have tremendous impact on their members' behavior including their continual commitment to their organization, their turnover decision, as well as their performance (Shaw et al., 2002; Shaw and Gupta, 2007). A particularly interesting question that recent research addresses concerns with the relationship between pay dispersion and the career outcome of employees, including their entrepreneurship behavior. Carnahan et al. (2012) study exactly this relationship and argue that organizations with highly dispersed wage structure compared to other organizations are likely to exhibit greater turnover of their employees to other incumbent firms particularly among low performing group of employees. Top performing employ-

ees of firms with highly dispersed wage structure are less likely to exit such structures because their outside opportunity is extremely limited and they are already rewarded more than other firms would be rewarding them had they changed employer. However, Carnahan and his colleagues argue that employees of firms with highly dispersed wage structure are more likely to create their own business if they decide to leave their employer. This is might be because of several confounding mechanisms: First high performing employees may have accumulated greater wealth throughout their career that in turn will reduce the financial constraint of starting a new venture (Evans and Jovanovic, 1989). Second, high performing employees may value non-pecuniary features of occupations such as autonomy and being your own boss which are common features of entrepreneurial occupations (Hamilton, 2000) more than low performing employees who are likely to value pecuniary rewards more than comfort or autonomy of the workplace. Second typically high pay dispersion in organizations is intended to induce employees to accumulate greater firm specific skills (Becker, 1962; Lazear and Rosen, 1981). Top performing employees at highly dispersed wage structures are likely the ones that have accumulated greater firm specific skill which will diminish in value if top performing employees leave to other incumbent firms. Nevertheless, top performing employees can retain almost all of their investment in firm specific skill if they leave to start their own venture and replicated learned routines and work related knowledge (Wezel et al., 2006). Hence as Carnahan et al. (2012) argue departures to entrepreneurship will be much more among top performing employees of firms with high wage dispersion compared to top performing employees of firms with compressed wage structures.

Organizational vital events. Brittain and Freeman (1986) performed the first study of the origins of Silicon Valley semiconductor producers from 1955 to 1981. They investigated organizational origins of 351 individuals who founded semiconductor production companies. Brittain and Freeman's seminal study is particularly interesting in a sense that they investigated organizational level characteristics that affected the

rate of spin-outs from those organizations. Brittain and Freeman investigated five organizational characteristics: (1) chief executive succession from outside of the firm, (2) acquisition of the firm by a non-semiconductor producer, (3) firm's rate of growth (4) degree of diversification (specialist versus generalist), (5) market pioneer (first entrant) in any of its product groups. The first two variables that Brittain and Freeman studied, points to the effect of vital changes in any organization's life course that is imparted on its employees. Changes in management brought by acquisitions and outside executive succession may change the structure of incentives inside the organization and prospects of advancement within the firm (Romanelli, 1989). Organizational vital events (sometimes called transformational events) change several characteristics of organizations including their culture, routines, and leadership style (Stuart and Sorenson, 2003) among many others during their life course. Such vital events may include CEO succession from outside of the firm (Brittain and Freeman, 1986), corporate acquisitions, or initial public offerings (Stuart and Sorenson, 2003).

Stuart and Soresnson (2003) studied how two vital organizational events, namely IPOs and acquisitions, change the ecology of competing organizations through internal organizational changes that they precipitate. For one thing IPOs and acquisitions bring a large sum of monetary rewards to the key members of an organization (e.g. CEOs or key scientists that have shares and stocks) which removes the financial constraints that hinders those members' attempts to found new ventures. To the extent that entrepreneurs are liquidity constrained (Evans and Jovanovic, 1989), IPOs and acquisitions remove monetary constraints of nascent entrepreneurs in existing companies. Apart from attenuation of financial constraints on members of an organization, IPOs and acquisitions may result in several qualitative changes inside the organization experiencing those events. Stuart and Soresnson (2003) identify several changes with respect to IPOs and acquisitions: (IPO). First IPOs change the power distribution within the firm by altering the size and membership of the board of directors, increasing the prominence

of the sales, marketing, and finance functions of the organization that may alter the priorities in the decision making process. Second, IPOs also impart performance pressures on organizations from the investors as organizations are expected to show short term financial performance. This performance pressure is likely to change distribution of resources among various functions of the organization (e.g. from R&D to sales and marketing). Third, as Stuart and Sorenson (2003) argue, IPO is a major event that characterizes a major change in an organizations structure. As an organization goes through IPO its level of bureaucratization may also increase as formal reporting and clear division of labor becomes a necessity as a result of increase in the complexity of the organization that IPO brings. All these changes from the organizations strategy to culture and structure that is brought by IPO may therefore alter the career expectations and interests of some members of the organization. Hence these changes can prompt organizational turnover during the IPO and possibly spin-outs by nascent entrepreneurs inside the organization. Similar to IPOs, acquisitions impart several qualitative changes to organizations. First Stuart and Sorenson (2003) argue that because typically large organizations acquire small target firms, acquisitions result in rapid change in the size of organizations and thereby sudden change in incentives and level of bureaucratization. In addition, the most salient impact of corporate acquisitions is probably the change it brings up in the corporate culture of the targeted firms (Cartwright and Cooper, 1993). This cultural mismatch exacerbates when the acquirer comes from a different industry than the target firm's industry. Stuart and Sorenson (2003: 181) note that When an acquirer differs demographically from its takeover target, acquirer and acquired share few common features: they likely operate under different norms, values, customs, cultures, human resource and compensation policies, levels of hierarchy and centralization, and so on. In these situations, the acquirers' efforts to impose its structure, systems, culture, values, or routines on the acquired organization will almost certainly give rise to resistance. As a result of mismatched organizational characteristics conflicts among

the members may emerge leading to turnover. Some of the turnover events may include entrepreneurship especially among more senior and key executive and scientific members of the organization.

Firms as structuring of worker's opportunities A different theoretical perspective on employee entrepreneurship observes firms as contexts that shape individuals' employment choices at each point in time. Sørensen and Fassiotto (2011) provide a brief conceptualization of this theoretical perspective. As Sorensen and Fassiotto describe looking at firms that simply structure the choices of individuals stand in sharp contrast with theoretical arguments that view firms as learning and training grounds, socialization and networking places, and shapers of beliefs and attitudes towards entrepreneurship. The core of this theoretical perspective is that organizations both independently and collectively shape the attractiveness of entrepreneurship.

Empirical findings: Agrawal et al (2004) studies several dimensions of entrepreneurial entry via spin-outs that includes reasons for their formation, development of their know-how, and their performance. Agrawal et al. (2004) traces the genealogies of firms in rigid disk drive industry from 1977 to 1997 and categorizes entrants as spin-outs if their founder had previously been employed in an incumbent disk drive producer. As noted in the theoretical framework of spin-out generation, Agrawal et al. posits that the imbalance between technological know-how of an incumbent firm with its market pioneering know-how will trigger spin-out generation. Measuring technological know-how with the areal density of each incumbent's disk drives and market pioneering know-how with active commercialization in each disk drive submarket (market for disk drives with different diameters) Agrawal et al. investigates the imbalance between the two dimensions and finds that those incumbents that have either high technological know-how or high market pioneering know-how generate more spin-outs. But those incumbents that have both high technological and market pioneering know-how are less likely to create spin-outs. Although Agrawal et al. (2004) argue that the imbalance between the two know-how

dimensions may increase frustration or entrepreneurial confidence in employees, these mechanism are unobserved and are not tested directly.

Besides Agrawal et al. (2004) that used product characteristics to measure technological know-how, other researchers have used more fine grained measure of knowledge using patents. Gompers, Lerner, and Scharfstein (2005) investigated entrepreneurial spawning of public firms from 1986 to 1999 in variety of industries including computer programming and data processing, computer and office equipment, drugs, communication equipment, surgical, medical, and dental instruments, electronic components and accessories, telephone communications, laboratory, analytical, and optical equipment, security brokers, dealers, and flotation, radio and television broadcasting stations, commercial banks, non-store retailers, special industry machinery (except metalworking). They used number of patents that is assigned to each incumbent in each year in either of the six patent categories defined by NBER (chemical patents, communication and computer patents, drugs and medical patents, electronic and electrical patents, mechanical patents, and other patents) as the stock of knowledge that each firm posses in each year in each patent category. Gompers and his colleagues regressed the total number of venture capital backed spin-outs that each public firm spawned between 1986 to 1999 on variety of firm characteristics including the stock of knowledge in each patent category and find that having more patents in computers and telecommunication and drugs and medical equipment significantly increases the likelihood of entrepreneurial spawning. Although the number of patents in these two NBER patent categories implies that the greater knowledge in computers and telecommunication and drugs and medical equipment is associated with greater entrepreneurial opportunities, it may also imply that these sectors are more favorable for venture capital investors which may in turn reflect greater likelihood of finding external financing for nascent entrepreneurs in public firms.

Klepper and Sleeper (2005) study the dynamics of spin-out generation in laser industry. They adopt a Hotelling-like model from Prescott and Visscher (1977) to allow for

spin-outs to enter product market niches. Their assumption is that firms that successfully invest in R&D create greater knowledge about the variants of products that can be targeted to different product niches. Their empirical analysis indeed shows that firms with more patents (proxy for knowledge about specific lasers) have greater likelihood of spin-out generation consistent with the argument that greater knowledge equates with greater variety of niches available in a firm's knowledge base. Nevertheless, it should be noted that Klepper and Sleeper make a strong assumption that there is a link between the amount of knowledge and variety of product market niches created. This may not be the case if a firm's investment in new knowledge is simply the refinement of its existing technology in the same product market niche. This is consistent with exploitation of existing capabilities in organizational learning (March, 1991). However, creation of product market niches in a firm's knowledge investment can be related to its knowledge generation strategies (e.g. exploration).

As noted in the theoretical arguments of employee entrepreneurship, organizational vital events, those major events during an organization's life course that impart severe changes to various characteristics of an organization, are likely to impact entrepreneurial behavior of the members of organizations experiencing those events. Stuart and Sorenson (2003) empirically investigated the effect of IPOs and corporate acquisitions on the likelihood of spin-out generation in the US biotechnology industry. Their findings support their hypotheses that IPOs of firms in high-tech industries and acquisitions of early stage technology based companies by demographically dissimilar firms increases the founding rates of new ventures around the time of these vital events. Klepper and Sleeper (2005) in their study of spin-outs in the laser industry also reported that acquisitions of laser producing firms by firms from other industries significantly increased the likelihood of spin-out generation.

A.2 Individual Level

In this section I review the recently growing literature that asks who leaves the incumbent firm for entrepreneurship? This literature is quite sparse and therefore the review will be limited to a small number of papers that address this question. One theoretical argument offered by Campbell et al. (2011) points out to the relative bargaining power between the employer and the employees. In their model bargaining power of employees over their employer hinges on their ability to recreate or transfer the firm's complementary assets to other incumbent firms. The firm's complementary assets may be comprised of organizational knowledge embodied as firm specific human capital in employees, codified routines, intellectual property, network of buyers and suppliers, brand etc. Campbell et al. (2011) argue that high ability employees have high bargaining power over their employer and may therefore transfer organizational routines, firm's clients, or other co-workers if they exit. Although high ability employees are well positioned to take advantage of their bargaining power Campbell and his colleagues argue that firms recognize their threat and reward them with various pecuniary and non-pecuniary benefits (Williams and Livingstone, 1994) and thereby reduce their likelihood of exit. A typical strategy for firms to keep their high ability employees is to share rents with them or pay them according to their performance to increase their perception of distributive and procedural justice (McFarlin and Sweeney, 1992) and increase the opportunity cost of leaving. As a result high ability employees will actually be less likely to leave their employers. Campbell et al (2011) embed entrepreneurship in the mobility decision of employees and asks where do employees go after leaving their employer? Do they go to existing incumbent firms or to found new ventures? They argue that employees' mobility decision depends on their ability to create value. According to Campbell and his colleagues high ability employees are more likely to found new ventures when they leave their current firm compared to low ability employees. They argue that it is top performing employees' ability to create optimal organizational structure that makes them

more likely to found new ventures. The set-up costs and risks associate with founding an organization will be lower for them. In addition, since high ability employees typically accumulate greater firm specific skills and resources relative to low ability employees they will experience greater challenges in integrating with organizational settings of existing incumbent firms and thereby are more likely to found new ventures.

In a related study, Carnahan, Campbell, and Agarwal (2012) also argue that high ability employees are more likely to leave to entrepreneurship than joining an existing incumbent firm but that depends on the pay structure of the firm as well. In other words, they argue that not all high ability employees are equally likely to found new venture and that depends on their employers' relative wage dispersion. In their argument wage dispersion conditions the exit decision of high ability employees in a sense that high ability employees of firms with highly dispersed wage structure are less likely to leave to other incumbents but if they leave they will be more likely to start their own venture mainly because the only way they can improve their rewards through mobility is by starting their own venture compared to high ability employees from firms with homogenous wage structure. In their view, high ability employees of firms with compressed wage structure can improve their rewards by moving to firms with dispersed wage structures.

Both Campbell et al (2011) and Carnahan, Campbell, and Agarwal (2012) test their hypothesis using an employer employee database of all the individuals working in the legal services industry in the United States. Their empirical analysis supports their theoretical arguments although their theoretical arguments are treated as unobserved.

A.3 Performance of Spin-outs

Apart from the large body of literature dedicated to investigating the underlying reasons for employee entrepreneurship, there is parallel literature devoted to comparison of the performance of spin-outs with other types of entrants into an industry. Besides spinning-out from an incumbent firm in the focal industry, other entrants could be classified

as either *de novo entrants*, meaning that their founders didn't have work experience prior to becoming entrepreneurs, *diversifying entrants* meaning that the firms existed in other industries before diversifying to the focal industry, or *incumbent backed entrants* meaning that they were affiliated with an incumbent firm in the focal industry with equity ownership of the incumbent firm in the entrepreneurial firm (Agarwal et al., 2004).

Studying performance is at the core of the strategy literature with a large body of research dedicated to understanding the sources of *competitive advantage*. Heterogeneity in firm performance is attributed to differences in firms' resources (Barney, 1991; Peteraf, 2006). According to the resource based view of the firm (RBV), a firm will enjoy sustained competitive advantage when its bundle of resources are valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). In fact one of the idiosyncratic resources that firms have is their *knowledge*. Firm knowledge may indeed satisfy all the attributes of RBV and hence it is considered as one of the corner stones of competitive advantage (Barney, 1991; Grant, 1996). How entrepreneurial firms acquire their knowledge and in what capabilities they differ therefore becomes crucial for studying the performance of new firms (Carroll et al., 1996; Klepper and Simons, 2000). Klepper and Simons (2000) in their study of the entrants in the U.S. television receiver industry find that the hazard rate of exit from the TV receiver industry is lower and the market share of the entrants is larger in the TV receiver industry if they had emanated from the firms producing home radios, the group of entrants that had the most relevant experience to the TV receiver industry. In fact the producers of home radios could leverage on their extensive marketing knowledge about home entertainment. As Klepper and Simons (2000) note home radio producers "had accumulated considerable information about improving and marketing radios that was likely to be useful for TVs, whose principal market was also home entertainment". Key to Klepper and Simon's (2000) model is the costs associated for innovation in the TV receiver industry which decreases with prior related experience

of the entrants in the industry. Brüderl et al. (1992) also build on human capital theory to show that prior industry specific experience of the founders of new firms improves the life chances of newly founded firms.

Although Klepper and Simons (2000) do not distinguish between spin-outs and other entrants, their study highlights the important mechanism of knowledge inheritance and knowledge transfer in explaining the superior performance of new firms. Recognizing the fact that new organizations often emerge from existing organizations (Stinchcombe, 1965) with founders' inherited knowledge inheritance as an important bridge between old and new ones, a number researchers from parallel streams of organizational sociology and economics attempted to investigate the consequences of knowledge inheritance and transfer on organizational outcomes such as structure, performance, and innovativeness. From organizational sociology perspective Phillips (2002) investigates the effect of parent-progeny knowledge transfer on survival of both progeny firms (spin-outs) and parent firms that spawned them. Phillips argue that organizations are comprised of a set of socially constructed routines, procedures, and resources that can be appropriated by employees when starting a business. Phillips moves further to argue that the impact of the transfer of resources and routines on organizations' survivability depends on the volume of transfer determined by the position of the founder in the parent firm. Using a sample of Silicon Valley law firms, Phillips (2002) shows that the higher the rank of the employees at their parent firm the lower the likelihood of their business failure. Phillips proxies the volume of routine and knowledge transfer with the rank of the employee. In a study of the US automobile industry, Klepper (2007) shows that spin-outs survive longer and perform distinctively than other group of entrants into the automobile industry. Klepper (2007) builds on the theoretical arguments of Klepper and Thompson (2010) in arguing that spin-outs are usually formed by better informed employees of incumbent firms who disagree with the strategic decision of other employees. Klepper (2007) therefore implies that it is the departure of talented employees that affect spin-out

performance. Nevertheless neither Klepper (2007) nor Klepper and Thompson (2010) show where the talent of the founder of the spin-out come from (e.g. from learning inside the firm or from innate ability or prior experience).

In studying rigid disk drive industry, Agarwal et al. (2004) also compare the performance of spin-outs with other group of entrants and denovo startups. They also confirm the hypothesis that spin-out perform distinctively than other group of entrants. Although Agarwal et al. (2004) argue that a variety of factors such as having insider knowledge about technological and marketing opportunities, access to valuable network of ties to industry constituents, and soical capital with other employees all together give spin-outs a performance advantage over other firms, they do not empirical tease these mechanisms. Nevertheless from Agarwal an her colleagues analysis it is possible to infer indirectly that at least inheritance of technological knowledge plays an important role in survival advantage of spin-outs over other entrants. Following chain of results let us infer that mechanism: greater technological knowhow of parent firms increases the likelihood of spin-out formation (an indication of knowledge inheritance or learning), technological knowhow of parent firms and spin-outs are related (an indication of knowledge transfer), spin-outs and new firms with higher technological knowhow are likely to survive longer.

Apart from the direct experience of the founders, performance advantage of spin-outs is likely to be related to the founders' ability to attract scarce resources to their newly founded firm. New firms usually have nothing more than the human capital of the founder and initial employees as well as enough financial resources to jump start the venture. Cooper et al. (1994) show that initial human capital and financial capital of entrepreneurial firms are important predictor of their performance. In particular financial resources seem to be an important source of capital for entrepreneurial firms. Cooper and his colleagues (1994) highlight that initial financial capital of entrepreneurial firms create "buffer against random shocks and allow the pursuit of more capital intensive strategies." (ibid, P. 1). The importance of financial resources for entrepreneurial firms is reflected

in the competition among founders in accessing to venture capital funds (Hsu, 2007). Nevertheless since information asymmetry and business uncertainty often characterizes young firms, the contracting between entrepreneurs and venture capital (VC) firms are fraught with moral hazard issues (Gompers and Lerner, 2001; Da Rin et al., 2011). In order to finance entrepreneurial firms VC's typically engage in extensive scrutinization of the business (Gompers and Lerner, 2001) and rely on credible signals on the quality of the firm (Hsu and Ziedonis, 2007). In particular, interorganizational affiliation (Stuart et al., 1999; Burton et al., 2002) can remedy part of the uncertainty surrounding new ventures when entrepreneurs should rely on their affiliated partners to signal the quality of their venture. In the study of the endorsement of entrepreneurial firms by investment bankers in biotechnology industry, Higgins and Gulati (2003) argue that entrepreneurial firms establish the legitimacy of their business through interorganizational affiliation of their upper echelon executives with prominent partners and pharmaceutical firms. Since spin-outs are naturally affiliated with established parent firms, the interorganizational affiliation of the founder will make it easier to secure external financing for their new venture. Chatterji (2009) examines time to funding in a sample of VC backed medical device firms and finds that spin-outs of existing incumbent firms are likely to secure VC financing faster than other non spin-out firms. Such faster access to funds combined with the knowledge and industry expertise that founders of spin-out bring result in their enhanced performance, faster commercialization of products, and higher valuations by investors (Chatterji, 2009).

Although it is fairly an established result that spin-outs outperform other entrepreneurial firms on a number of dimensions, performance heterogeneity within the sample of spin-outs is relatively less researched. Notable exceptions are the works of Hvide (2009), and Sørensen and Phillips (2011). These studies look at the proxy characteristics of employer size on the performance of spin-outs. Employer size (simply defined in the literature as small and large) can have differential effect on the performance of spin-outs. This is

because size proxies a variety of factors that are not only related to the likelihood of spin-out generation (Sørensen, 2007a; Elfenbein et al., 2010) but also to the likelihood of success of spin-outs. Employer size can be a proxy for the incentive structure (structure of wages) of incumbent firms especially in high technology sectors. In particular it appears that firm size has a negative relationship with the pay for performance structure (Schaefer, 1998). Literature on agency theory and incentive structure (Holmstrom, 1989, 1992) argue that decreasing pay for performance sensitivity with firm size is a result of trading off risk associated with the business with incentives to remain in the firm. Small firms that bear greater uncertainty and risk of dissolution therefore would link wages more closely to the marginal ability of workers. Building on this observation Hvide (2009) develops a theory of entrepreneurial quality which directly links the quality of spin-outs to the size of the parent firms. The driving assumption in Hvide's (2009) theoretical model is that small firms can directly link pay structure to the human capital of workers whereas large firms can only set up an optimum cut-off wage schedule because of informational disadvantages of large firms in monitoring the ability of their workers. Such a differentiation in small and large firms' wage structure would result in higher quality entrepreneurs emanating from large firm compared to small firms. Stated simply since employees of small firms receive pay for performance only the worst employees (or employees with private benefits) leave to become entrepreneurs whereas in large firms a cut-off wage implies that employees whose utility from their ability falls above the cut-off wage, therefore highly talented ones, will leave to become entrepreneurs. Using an employer employee matched dataset from Norway, Hvide (2009) confirms this hypothesis and shows that parent firm size is positively associated with spin-out's operating returns on assets and its growth. Surprisingly, Hvide (2009) reports negative relationship between firm size and spin-out's survival albeit being statistically insignificant.

Sørensen and Phillips (2011) also study the effect of firm size on the success of spin-outs and surprisingly drive contradictory results to Hvide (2009). Sørensen and

Phillips argue that increase in organizational size is equal to increased division of labour, task specialization, and narrowly defined jobs. These structural characteristics of large organizations inhibit the development of entrepreneurial skills among their employees. Lazear (2005) argues that one of the defining characteristics of entrepreneurs is that they are jack-of-all-trades. According to Lazear (2005) successful entrepreneurship requires developing a mix of skills. Sørensen and Phillips also argue that knowledge and routines that employees inherit from large firms “may not be suited to entrepreneurship, which typically requires flexibility and adaptation.” (ibid, P. 1281). All together Sørensen and Phillips (2011) argue against employer size and performance advantage of spin-outs. They test their prediction using the Danish employer employee matched dataset and find that spin-out founders emanating from large firms generate lower entrepreneurial income than founders emanating from small firms.

Transfer of knowledge and resources makes parents and spin-out firms structurally similar. Phillips (2002) shows the similarity in practice areas of law firms when partners of existing law firms spin-out to start their own law firm. Studying spin-out process in the laser industry, Klepper and Sleeper (2005) argue and empirically show that spin-outs initially produce the same type of laser as their parents produced. This confirms the imprinting effect of organizations on their employees as stated by Stinchcombe (1965).

B Exact Least Square Estimation with Conjugate Gradient Algorithm

Below is a brief description of the conjugate gradient algorithm (CGA) which is fully described in Hestenes and Stiefel (1952). Abowd et al. (2002) also describe CGAs use in the analysis of employer-employee data sets. CGA is an iterative method for solving a large system of linear equations of the following form,

$$Ax = b \tag{B.1}$$

where x and b are known vectors and A is a square, symmetric, and positive definite matrix. CGA is an iterative algorithm that converges to the exact solution of equation (B.1) in n steps. The optimization process starts with the initial arbitrary point x_0 and takes a series of steps x_1, x_2, \dots, x_n each of which is a new solution to (B.1). The procedure stops when the final solution, say x_n , is close enough to the exact solution of (B.1) namely x^* . The mechanics of the steps are as follows. Define $e_i = x_i - x$ as a vector that indicates how far we are from the exact solution. Also define the residual $r_i = b - Ax_i$ as a vector that indicates how far we are from the solution to (B.1). CGA therefore accomplishes convergence when $r_i \approx 0$.

Each new solution x_1, x_2, \dots, x_n , is generated by a search *direction*, d_i , in the solution space as follows:

$$x_{i+1} = x_i + \alpha_i d_i \tag{B.2}$$

The value α_i is found using the intuition that e_{i+1} should be orthogonal to d_i . Using this orthogonality condition α_i is generated as follows:

$$d_i' e_{i+1} = 0 \tag{B.3}$$

$$d_i'(e_i + \alpha_i d_i) = 0 \tag{B.4}$$

$$\alpha_i = \frac{d_i' e_i}{d_i' d_i} \quad (\text{B.5})$$

As it is evident in the above equation, the value of α_i requires knowing of the error e_i . Since the optimal solution x^* is unknown e_i is not identified. CGA therefore proceeds by creating a new search direction, d_{i+1} that is *conjugate* to the existing search direction d_i . The term conjugate means that the vectors d_{i+1} and d_i become orthogonal with respect to matrix A :

$$d_i' A d_i = 0 \quad (\text{B.6})$$

Conditional on the two search directions being A-orthogonal the value of α_i is obtained by:

$$\alpha_i = \frac{d_i' A e_i}{d_i' A d_i} = \frac{d_i' r_i}{d_i' A d_i} \quad (\text{B.7})$$

where the residual r_i is a known vector since $r_i = b - A x_i$. After obtaining a new solution x_{i+1} , CGA iterates as above by generating a series of solutions until the residual $r_n \approx 0$ or a pre-specified number of iterations is reached.

C Multiple Choice Models

In multiple choice models, often times, the outcome is the realized choice of the individual among several alternatives. The outcome can be formulated as numerical variables such as 0,1,2,... corresponding to each choice. This structure of the multiple choice models are usually motivated by random utility models.²⁶ Formally the random utility model for individual's alternative choices can be expressed by,

$$U_{ij} = x_i\beta_j + \epsilon_{ij} \quad (\text{C.1})$$

where the individual i 's utility from choice j is related to her characteristics, x_{ij} .²⁷ The probability that individual i chooses alternative j therefore will be,

$$P[Y_i = j] = P[U_{ij} > U_{ik}] \quad \text{for all } k \neq j \quad (\text{C.2})$$

Above equation relates the probability of observing choice j for individual i to the probability that her utility from choosing j exceeds the utility from all other choices. McFadden (1973) shows that when the disturbances, $\epsilon_{ij} = (\epsilon_{i1} \dots \epsilon_{ik})$, across alternative choices are independent and identically distributed according to the type I extreme value distribution (Gumbel),

$$F(\epsilon_{ij}|x_i) = e^{-e^{-\epsilon_{ij}}} \quad (\text{C.3})$$

then the probability of observing each alternative becomes,

$$P[Y_i = j] = \frac{e^{x_i\beta_j}}{\sum_{k=1}^j e^{x_i\beta_k}} \quad (\text{C.4})$$

Since in multinomial logit explanatory variables (x_i) are constant across alternative choices - individual characteristics do not vary across choices - the only way they can affect the choice probabilities is by having a differential impact on the choice alternatives.

²⁶The econometric specification is sometimes called latent variable model.

²⁷The term "random" in the random utility model is because of the inclusion of the disturbance, ϵ_{ij} , in the utility function.

Therefore multinomial logit estimates $j - 1$ coefficients and one coefficient (β_j) will be redundant. Normalizing the redundant coefficient to $\beta_0 = 0$ and taking out of the sum in the denominator of the equation (C.4) results in,

$$P[Y_i = j] = \frac{e^{x_i \beta_j}}{1 + \sum_{k=1}^j e^{x_i \beta_k}} \quad (\text{C.5})$$

Coefficients of the above model is difficult to interpret. As a result most often the results are represented as log-odds ratios. Assuming that there are $j + 1$ alternative choices, from equation (C.5) we can compute J log-odds ratios,

$$\ln\left[\frac{P[Y_i = j]}{P[Y_i = k]}\right] = x_i(\beta_j - \beta_k) \quad (\text{C.6})$$

It is clear that the coefficients of equation (C.6) can be interpreted easily.

Essays on Employee Entrepreneurship

Abstract: This dissertation consists of three essays on employee entrepreneurship where some employees leave paid employment to start their own business. In particular I examine the antecedents of such entrepreneurial transitions from contextual and individual perspectives. In the first essay I examine why historically best performing firms generate more entrepreneurs than other firms. In the second essay I investigate the relationship between matching in the labor market and entrepreneurial transition of employees. The empirical setting of the first two essays is the whole population of Swedish workers from 1990 to 2007. In the third essay I investigate the effect of organizational exploration and exploitation on employee entrepreneurship in medical devices industry. The overall conclusion of this dissertation is that context matters for entrepreneurship. In addition, sorting in the labor market and fit between an employer and employee determine who becomes an entrepreneur.

Keywords: Employee Entrepreneurship, Matching, Sorting, Exploration, Exploitation.

Essays on Employee Entrepreneurship

Abstract: Cette thèse rédigée sous la forme de trois articles explore les antécédents de l'entrepreneuriat, c'est à dire le choix d'individus de quitter leur travail salarié pour créer leur propre entreprise. Le premier chapitre examine les raisons pour lesquelles les entreprises les plus performantes génèrent plus d'entrepreneurs que leurs concurrents ne le font. Le deuxième chapitre étudie la relation entre l'appariement salarié-organisation sur le marché du travail et la transition vers l'entrepreneuriat. Au plan empirique, ces deux premiers chapitres exploitent une base de données sur le lien employeurs-employés en Suède (1990-2007) et s'appuient sur une méthodologie originale pour différencier les effets dus à la qualité individuelle du salarié, la qualité de l'entreprise, et l'appariement salarié-entreprise. Le troisième chapitre de cette thèse étudie au niveau organisationnel les effets des stratégies d'exploration/d'exploitation dans l'industrie des appareils médicaux. Cette thèse tend à montrer que le contexte ainsi que le processus d'appariement et de sélection jouent un rôle important dans le choix de devenir entrepreneur.

Mots clés: entrepreneuriat, modèles d'appariement, exploration, exploitation.