Human Capital in Newly Established Firms

Four Empirical Investigations

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Contents

List of papers

The thesis comprises extended versions of the following papers:

1. "Academic Spin-off's Transfer Speed – Analyzing the Time from Leaving University to Venture," *Research Policy*, 39 (2), 189–199.

2. "Employment Growth in Newly Established Firms – Is There Evidence for Academic Entrepreneur's Human Capital Depreciation?," ZEW Discussion Paper 09-050, Mannheim.

3. "Entry Strategies, Human Capital, and Start-Up Size," *International Journal of Entrepreneurship and Small Business*, forthcoming, joint with Sandra Gottschalk and Michaela Niefert.

4. "Heterogeneous Labor Demand of Newly Established Firms", unpublished manuscript.

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Abbreviations

BA	Federal Employment Agency (Bundesagentur für Arbeit)
CIS	Community Innovation Survey
FRG	Federal Republic of Germany
fte	full-time equivalents
GEM	Global Entrepreneurship Monitor
GRD	German Democratic Republic
ICT	Information and communication technologies
KfW	Kreditanstalt für Wiederaufbau, a state-owned German bank with tasks on behalf of the state
MUP	Mannheim Enterprise Panel
NACE	Statistical Classification of Economic Activities in the European Community (Nomenclature statistique des activités économiques dans la Communauté européenne)
NB	Negative binomial regression
OLS	Ordinary least squares
R&D	Research and development
U.S.	United Staates (of America)
UK	United Kingdom of Great Britain and Northern Ireland
ZEW	Centre for European Economic Research

1 General introduction

Around 237,000 new firms have been founded in Germany each year during the last decade. Investigating start-up conditions and start-up success is an important concern of economic research, since the establishment of new firms is seen as a major driver of economic growth. As Baumol, who won the Global Award for Entrepreneurship Research in 2003, notes, “if we seek to explain the success of those economies which have managed to grow significantly with those that have remained relatively stagnant, we find it difficult to do so without taking into consideration differences in the availability of entrepreneurial talent and in the motivational mechanisms which drives them on” (Baumol, 1968, p. 66). New firms speed up structural change, foster market development and product variety by introducing new products and services, and they enhance competition in existing markets.

Since all highly-developed countries face the challenges of competition among knowledge-based economies, the importance of knowledge for securing an economy’s competitive advantage has been increasing over time. Hence, European policy makers agreed in 2000 to the Lisbon Strategy. The major aim of this 10 year plan was to make Europe “the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion” (European Council, 2000). Within the long list of Lisbon Agenda’s targets, Europe should create a friendly environment for starting up and developing innovative businesses. Also, in the new 10 year plan recently presented by the European Commission - the “Europe 2020 Strategy” (European Commission, 2010) - common targets laid down in the Lisbon Agenda remain present.

Fostering firm formations and creating favorable start-up conditions has thus been an important concern of economic policy programs in Germany for many years. A bulk of policy programs launched by the federal government and the federal state governments provides support for all kind of firm formations in terms of subsidized start-up consultancy or start-up financing.

Although people often refer to entrepreneurship as innovative entrepreneurship in the Schumpeterian sense of “creative destruction”, entrepreneurship - in its wide sense -

is the establishment of any kind of new firm, be it a small restaurant or a high-tech start-up. According to that view, entrepreneurs are for the most part business innovators. The innovation may be a crucial one such as introducing new products based on nanomaterials, but also may be a minor one such as starting the first Chinese snack bar within a suburban area (Lazear, 2004).

New firm foundations received a special attention since the studies of Birch in the 1980's (Birch, 1979, 1981, 1987), who claimed that during 1969 and 1976, about two thirds of all new jobs in the U.S. have been created by small and young firms with less than 20 employees. While the extent to which start-ups generate employment has been widely debated in the aftermath of Birch's studies (Storey, 1994; Davis et al., 1996), there is still a wide academic interest in assessing the importance of new firms for creating sustainable employment.

Studies in this field have mainly investigated aggregate employment effects. One can distinguish between direct employment effects, which is the employment created within new firms, and indirect employment effects, which are the employment effects induced by new firms in incumbent firms.

Usually, direct employment effects are investigated by following the evolution of employment in yearly cohorts of new firms. Total employment in cohorts of newly established firms typically increases in the first year, but after one or two years, total employment considerably declines due to exiting start-ups. After 6 to 8 years, it falls below its initial level (Fritsch and Weyh, 2006; Wagner, 1994; Boeri and Cramer, 1992). In a nutshell, there are two reasons for the rapid decline of total employment in start-up cohorts. First, there is a high risk of failure of new firms and about half the firms leave the market within the first five years of operations. Second, the majority of non-exiting start-ups remain rather small.

Recent research has tried to account for indirect supply side effects. Positive indirect employment effects are driven by securing efficiency, the acceleration of structural change, amplified innovation and innovative entry. Negative indirect effects might occur because of crowding out of incumbents which are forced to downsize or to exit. Though successful new firms should be more productive than exiting incumbents, the increase in productivity might be labor-saving (Fritsch and Müller, 2004). If indirect effects are taken into consideration, statistically significant effects of firm foundations on regional employment can be found up to 10 years. While in the first year, the total effect on employment is positive due to new capacities build up by new firm entries, the effect becomes negative after the first year due to exiting capacities. After 5 to 6 years, positive supply-side effects induce a positive total effect (Fritsch and Müller, 2004; Acs and Müller, 2008).

Indeed, the main driver for productivity growth and net employment growth is a small group of high-potential start-ups, called "gazelles", which survive and grow substantially (Henrekson and Johansson, 2009). Research at the individual firm-level has thus investigated determinants of start-up survival and firm's employment growth.

Studies which investigate employment creation at the firm level are numerous, but focused specifically on assessing the importance of a few drivers of employment growth in the first years of a firm's operations. Several firm-specific, founder-specific and industry-specific factors have been found to be important predictors of young firms' labor demand. Especially the founder's human capital turns out to be a major predictor of survival, start-up size and employment growth in young firms. Human capital refers to the competences and knowledge embodied in persons and has long been recognized as an important factor of production, both in macroeconomic studies (e.g. the new growth theory) and microeconomic studies. Returns to investment in human capital have been the foundations on which most microeconomic studies have been investigating human capital accumulation with major contributions of Mincer (1974), Becker (1993) and Griliches (1977). Lazear (2004) has integrated the concept of differentiated human capital into a theoretical framework of the choice to become an entrepreneur.

A group of special interest are start-ups in the research- and knowledge-intensive industries which are founded by university graduates and researchers. In particular, some policy programmes in Germany (e.g. the EXIST programmes) are conducted with the intention to increase the number of these academic start-ups. By means of academic start-ups, technology transfer, i.e. the commercialization of knowledge developed within the university, shall be enhanced.

Start-ups in the research- and knowledge-intensive industries cover about 23 percent of all firm foundations in Germany (see Figure 1.1). This amounts to an average of about 59,000 German start-ups in the research- and knowledge-intensive industries each year.

Research- and knowledge-intensive industries comprise high-tech manufacturing firms as well as firms in technology- and knowledge-intensive services. High-tech manufactur-

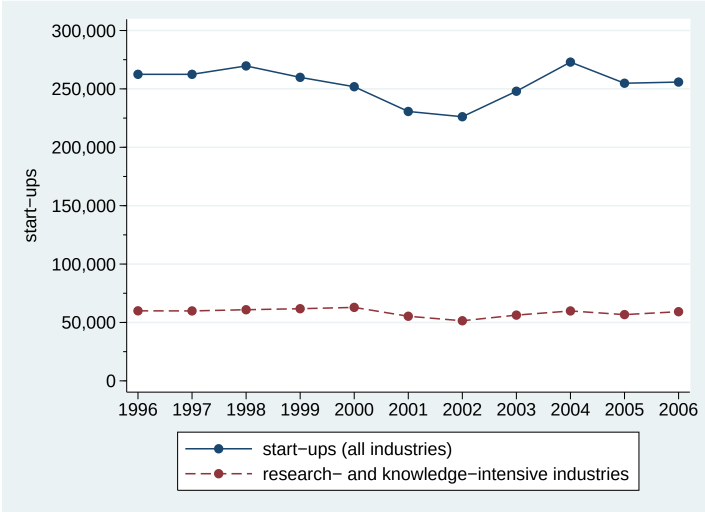


Figure 1.1: Start-ups in all industries

Source: ZEW Spin-Off Survey 2001 and 2008, MUP.

ing industries are those industries which largely engage in R&D activities. Examples are manufacturing sectors which produce pharmaceutical and chemical products, mechanical engineering, electronics and communication equipment, computers, automobile and transportation equipment or precision and optical instruments. Technology-intensive services strongly rely on new technological products, e.g. software programming, telecommunications or physical and chemical analysis. Knowledge-intensive services comprise business and tax consulting, advertising, legal activities and social science research and development services. Founders' human capital is of special importance in these industries. More than half of the firms are start-ups by students, graduates or academic researchers. The majority of these "academic start-ups" are set up by students and graduates (around 27,000 German start-ups each year). Researchers have established around 7,000 start-ups yearly in Germany (see Figure 1.2).

While the burst of the "dotcom bubble" in 2000 is clearly visible in declining start-up numbers for academic start-ups by students and graduates, it is less visible for start-ups of academic researchers due to scaling effects in Figure 1.2. However, start-up numbers for new firms established by academic researchers declined by 29 percent between 2000 and 2002.

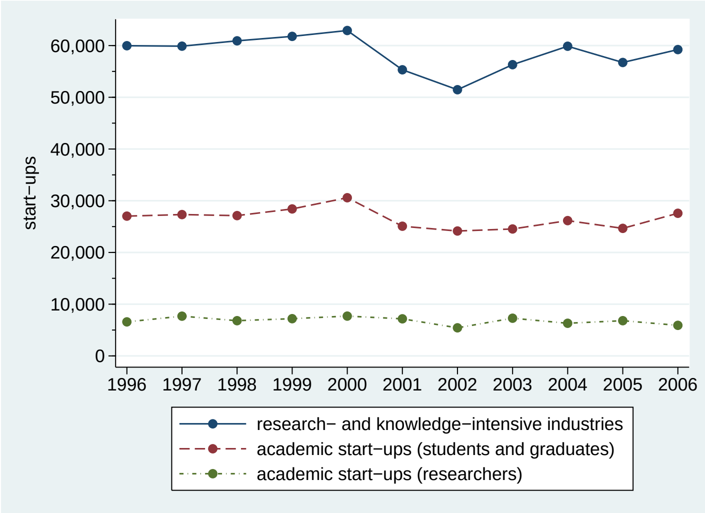


Figure 1.2: Firm foundations in the research- and knowledge-intensive industries

Source: ZEW Spin-Off Survey 2001 and 2008, MUP.

When investigating start-ups in the research- and knowledge-intensive industries, a special focus is placed on technology transfer. Firm foundations of academic persons are an important channel of commercializing new knowledge developed within the public research sector. If some kind of technology transfer has effectively taken place, one refers to such start-ups as academic spin-offs.

Academic spin-offs can be distinguished further according to the type of technology transferred. Transfer spin-offs are academic start-ups which transferred new research results or newly developed methods into marketable products, while in case of competence spin-offs, skills acquired in academia have been transferred from the university into the business idea of the new firm. Start-up numbers of academic spin-offs have been rather stable over time. Each year, about 7,000 spin-offs are founded, most of them are competence spin-offs (see Figure 1.3).

The majority of academic spin-offs in Germany originates from German universities. But when comparing spin-off intensities, universities of applied sciences are the most important incubators of academic spin-offs (2 spin-offs per year for each 100 scientists), closely followed by technical universities and universities (1.5). Except of institutions of the Fraunhofer Society (1.4), public research institutions have rather low spin-off

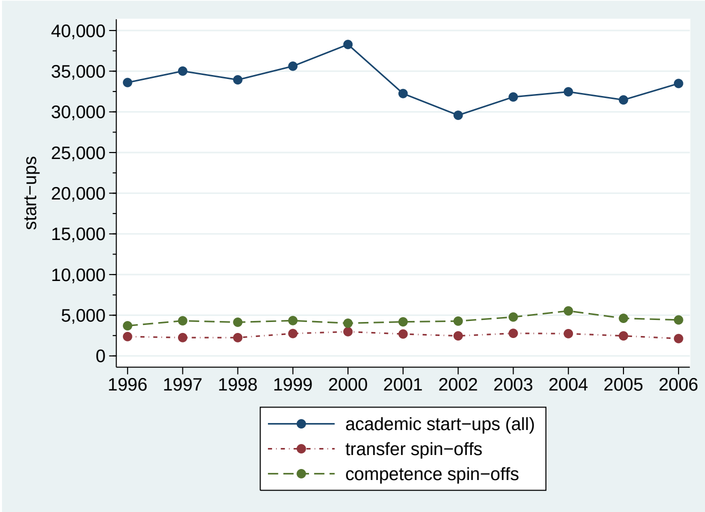


Figure 1.3: Spin-off establishments

Source: ZEW Spin-Off Survey 2001 and 2008, MUP.

intensities (0.3 to 0.6). Spin-offs largely engage in R&D and often have ongoing contacts with academia (Egeln et al., 2003a).

This thesis provides a detailed look at employment in newly established firms within the context of human capital. The thesis is a collection of four self-contained empirical investigations at the firm level, which contribute to the literature on technology transfer and job creation of newly established firms. The main object of investigation throughout all chapters is the importance of human capital in newly established firms. Chapter 2 and chapter 3 contain two empirical investigations on the specific topic of academic spin-offs and academic start-ups in the research- and knowledge-intensive industries in Germany. The analyses in the fourth and fifth chapter are further broadened. In these chapters, I do not only investigate academic start-ups, but newly established firms in nearly all industries.

Three different large-scale computer-assisted telephone surveys of new firm foundations in Germany conducted by the Center of European Economic Research have been used as underlying data sets. All samples were drawn from the population of newly established businesses collected in the Mannheim Enterprise Panel (MUP). This panel is built upon semi-annual information on all economically active firms provided by Creditreform, Germany's largest credit rating agency. The different surveys will be described in detail in the respective chapters of this thesis.

A study of Egeln et al. (2003a) revealed the surprising fact that 50 percent of all German academic spin-offs founded between 1996 and 2001 were established 4 years or more after the founder left his academic institution. Since this phenomenon has been neglected in the literature before, chapter 2 tries to identify the drivers of the time from leaving academia to founding an academic spin-off. I propose an explanation for those time-lags which is based on the existence of complementarities in skills and the type of knowledge sought to be transferred. In fact, the duration analysis of chapter 2 reveals that a longer time-lag is caused by the necessity of assembling complementary skills, either via acquisition by a single founder or via searching for suitable team members. Furthermore, new ventures are established earlier if there has been high-level technology transfer. Some further interesting results appear from the inclusion of variables which capture support from academic institutions. Spin-off establishment is substantially accelerated if the founders have access to university infrastructure, or receive informal support by former colleagues.

The third chapter of this thesis investigates start-up success of all academic start-ups as measured by young firms' employment growth. Chapter 3 is directly linked to the second chapter since a special focus is placed on the consequences of the time-lag after leaving university on employment growth within the firm. I propose and test an explanation which is based on two components of academic entrepreneurs' human capital: the development of a founder's academic knowledge and the development of his professional experience. Due to an accumulation of professional experience and a depreciation of academic knowledge, the impact of the time between leaving university and founding a firm should be inverse u-shaped. Since academic knowledge should be more important in case of academic spin-offs, I test for differences between ordinary academic start-ups and transfer spin-offs. In order to get a more comprehensive picture of the determinants of academic start-ups' employment growth over the whole distribution of growth rates, quantile regressions are conducted. Besides giving a more complete picture of the distribution than mean-based regression techniques, quantile regressions have the advantage of an inherent robustness to outliers. This is an appealing characteristic if one is especially interested in the tails of the distribution, here non-growing and highly growing firms. Additionally, further determinants of young firms' employment growth (e.g. firm size and age, innovation activities or internationalization) are examined along the whole distribution of growth rates. The results indicate that human capital depreciation is of crucial importance for both academic start-ups and academic spin-offs, the founder of the latter suffering even more from human capital depreciation.

In chapter 4, I look at the determinants of new firms' start-up size. Start-ups of almost all industries, i.e. manufacturing firms, both high-tech and low-tech, service firms of all types, retail and wholesale firms, and construction firms, are examined. Since earlier studies found that both survival prospects (Audretsch and Mahmood, 1995; Geroski et al., 2007) and employment growth of young firms (Lotti et al., 2009; Almus and Nerlinger, 1999, 2000) tend to be linked to a firm's start-up size, a better understanding of the factors influencing start-up size is crucial. Most of the rare literature on initial firm size focuses on industry characteristics. This chapter contributes to the understanding of the determinants of initial firm size by analyzing firm specific factors such as founders' human capital composition and entry strategies. Following Becker (1993), founders' human capital is divided into generic and specific human capital. While generic human capital refers to the general knowledge acquired through formal education and professional experience, specific human capital comprises skills that can be directly applied to the entrepreneurial job. Human capital will both have an influence on the optimal initial size and on resource constraints which determine actual start-up size in conjunction. As a main novelty in the literature of start-up size, entry strategies are introduced as a potential determinant of initial size. Entry strategies are captured by using information on the firms' activities in research and development and on the major motive for firm formation. These are entry based on innovation, opportunity entrepreneurship, necessity entrepreneurship, independency entrepreneurship and spin-out entrepreneurship. Entry strategies are expected to largely influence optimal initial size and the resulting start-up size.

Start-up size is measured by the number of employees at the point in time when the firm was started. Regression analyses are conducted for start-up size measured in full-time equivalents and head counts. The regression results indicate that in addition to industry effects, start-up size is considerably influenced by entry strategies and the human capital of firm founders. Firms conducting R&D continuously start larger than others, when measuring initial employment in full-time equivalents. However, the effect is not significantly different from zero if start-up size is measured in head counts. This suggests that R&D tasks are mostly carried out by full-time employees and to a lesser extent by persons working part-time for the firm. Further, firms with entry strategies based on the exploitation of new market opportunities as well as spin-out entrepreneurship exhibit a higher initial size while start-ups established from necessity appear to start at a smaller scale. Having a university degree and general work experience, as measured by the founder's age, exerts a positive influence on start-up size. Concerning specific human capital, start-up size is larger if the founders have been successful as an entrepreneur previously or if they gained managerial experience in dependent employment. Altogether, specific human capital tends to have a larger impact on initial size than generic human capital.

After investigating start-up size and early employment growth in the previous chapters, the quality of jobs created in young entrepreneurial firms is of special interest in chapter 5. Until recently, studies analyzing the structure of the workforce in newly established firms are rare and solely descriptive (Gottschalk et al., 2008; Weißhuhn and Wichmann, 2000). In order to fill that research gap, chapter 5 aims to identify the determinants of labor demand for different levels of employees' education. The analysis falls back on work which has been done in order to analyze heterogeneous labor demand of matured firms (Bond and Van Reenen, 2007). Analyzing heterogeneous labor demand for matured firms is mainly motivated by the rapid decline in relative demand for unskilled labor over the last three decades, higher skill-premia for high-skilled employees and rising unemployment among the unskilled.

A prominent explanation for these facts has been the hypothesis of a skill-biased technological change, which is a shift in the production technology that favors skilled over unskilled labor (see Violante, 2008). Most microeconometric evidence is in favor of a skill-biased technical change since new technologies seem to be complements with skilled employees (Autor et al., 2003; Autor and Katz, 1999; Autor et al., 1998). I extend the common framework of analyzing heterogeneous labor demand of Bond and Van Reenen (2007) to characteristics which especially apply for young firms by introducing the generic and specific human capital of the firm's founders as an additional factor of production. Products and services offered by young and small firms are strongly connected to the founder's personal characteristics. The generic and human capital will largely determine the business concept, the type, and sophistication of a firm's products and services. Since highly specialized products will require a firm's employees to have certain skills, labor demand should vary between founders who differ with respect to their generic and specific human capital.

The augmented model of heterogeneous labor demand is empirically estimated using models of corner solution outcomes. Thereby, I asses the impact of founder's human capital on heterogeneous labor demand in newly established firms. The different models of corner solution outcomes are presented and compared according to their appropriateness. The chosen models identify entrepreneurs' human capital as a major determinant of the qualification structure in young firms. Furthermore, the hypothesis of a skill-biased technical change has been tested and confirmed for the very first time for young firms.

The thesis as a whole thus provides a comprehensive view on human capital as a factor of production in newly established firms. Knowledge generated in public research institutions can lead to new business concepts and products offered by new firms. Besides having a look at the determinants of technology transfer speed, I investigate the influence of founders' human capital on how large new firms start operations, on which type of labor they demand, and on academic start-ups' early employment growth.

2 Academic spin-off's transfer speed

2.1 Introduction

Technology transfer from public research institutions, i.e. the commercialization of research results, can take place through many different channels. One important channel is the formation of new firms which are based on research, knowledge or skills generated in these institutions.[1] Bercovitz and Feldmann (2006) identify the establishment of those firms, known as academic spin-offs, as one of the core mechanisms of university technology transfer besides sponsored research, licensing out of R&D results and hiring of students or researchers. Technology transfer can also proceed through other channels such as the adoption of tacit knowledge or publications.

For licensing, Jensen and Thursby (2001) find that inventions are so "embryonic" at the time of licensing that it is not known whether the invention will become successfully commercialized. Most inventions require further development. In this development process, inventor cooperation is crucial for commercial success. However, because of a moral-hazard problem with regard to inventor's effort, there will be no further development unless the inventor's return and the licensee's output are linked. Jensen and Thursby propose royalties or equity participation as possible solutions to the moral-hazard problem. Academic spin-offs might be another solution to that kind of moral-hazard problems in technology transfer.

Other studies analyze why transfer channels often suffer from a low speed of technology transfer. Adams (1990) shows that there is an average lag of 20 years from the publication of academic research to its application by industry, whereas Mansfield (1995) finds that for a firm's product or process innovations, which could not have been developed in the absence of recent academic research, on average 7 years elapse between the finding of the relevant academic research results and the commercial introduction of the new product or process.

[1] Public research institutions include apart from higher education institutes (e.g. universities or technical colleges) public research organisations (e.g. Fraunhofer Society, Max Planck Society). In the following university, academia and public research institutions are synonyms.

When examining academic spin-offs, one comes across a wide variety of spin-off definitions throughout the literature. While some definitions focus on the founder(s) to be employees (or even just students or alumnis) of a public sector research institution, other studies occasionally allow for surrogate entrepreneurship and focus on the aspect of technology transfer. In that case, a key technology needs to be (formally) transferred from academia to the start-up (see Kreijen and van der Laag, 2003). A very comprehensive survey of spin-off definitions can be found in Pirnay et al. (2003). Most studies (e.g. Steffensen et al., 1999; Smilor et al., 1990) follow an approach which Clarysse and Moray (2004, p. 59) term to be the common two-dimensional approach: An academic spin-off "is a new company that is formed (1) by a faculty member, staff member, or student who left university to found the company or started the company while still affiliated with the university, and/or (2) a core technology (or idea) that is transferred from the parent organization". In this study, I follow the approach proposed by Pirnay et al. (2003, p. 356) and define spin-offs as "new firms created to exploit commercially some knowledge, technology, or research results developed within a university". This definition is basically the common two-dimensional approach which extends the second dimension. This approach does not solely include formally transferred technologies but also scientific as well as technical skills acquired during a person's academic activities. However, academic founders must have declared their academic knowledge as indispensable for firm foundation.

There is a prevalent belief that academic spin-offs are established when the founder is employed at university or directly after the founder has left the academic institution. In a nutshell, Carayannis et al. (1998, p. 3) state the naive view: "Typically, an employee [. . .] leaves the parent organization, taking along a technology that serves as entry ticket for the new company in a high-tech industry." In fact, there is no common statement in the definitions of academic spin-offs about the timing of the business foundation. Some definitions even explicitly state that academic spin-offs are only those new ventures which have been founded during the time at the research institution or immediately after leaving science (e.g. Pirnay et al., 2003). But substantial technology transfer from academia can take place even years after a founder has left university (Egeln et al., 2003a). Early research even includes those ventures which are not founded immediately, as Pirnay et al. (2003) note:

> "Roberts considered a venture as a MIT spin-off even if there was a lag of up to nine years between leaving MIT or an affiliate labs and starting the

> company as long as the technological base of the company was related to research at the lab at the time of employment. (McMullan and Vesper, 1987, p.356)"

Although it is well known that spin-off companies can be started years after having left university, the analysis is mostly restricted to the firms the founders of which are still members of the university or have left very recently (e.g. Druilhe and Garnsey, 2004). In the first study for Germany, which tried to reveal both the scope of academic spin-off activities as well as the characteristics of academic spin-off firms, Egeln et al. (2003a) found that one of three spin-offs are established more than five years after the founder has left the public research institution.

In this chapter, I analyze the factors that have an influence on the time dimension in the establishment of academic spin-offs. A special focus is put on the existence of complementarities in skills needed to establish spin-off ventures as well as on the impact of the character of technology transferred. In a duration analysis framework, I will show that a longer time-lag is caused by the necessity of assembling complementary skills, either via learning by a single founder or by searching for suitable team members. Furthermore, I find that new ventures are established earlier if high-level technology transfer has taken place, if the founders have access to university infrastructure, or if they received informal support by former colleagues.

This chapter proceeds as follows: The introduction is followed by a short review of existing empirical spin-off literature. Afterwards, the hypotheses for the empirical analysis are developed. Section 2.4 carries out the empirical analysis and section 2.5 summarizes the findings and concludes the chapter.

2.2 Literature review

During the last few years a wide range of studies about the formation, characteristics and development of academic spin-offs evolved from the literature on the commercialization of academic research. The following review on the literature about academic entrepreneurship aims to enable the reader to put the investigation of the time from leaving university to venture into a broader context. For a more comprehensive review on the spin-off literature see Djokovic and Souitaris (2008), O'Shea et al. (2008) or Mustar et al. (2006).

The spin-off literature covers a wide field of different topics. Many studies investigate the spin-off phenomenon at the university level. These studies often take a policy view and ask how a region or university can enhance and facilitate spin-off activities (e.g., O'Shea et al., 2005; Powers and McDougall, 2005; Clarysse et al., 2004; Lockett et al., 2003; Franklin et al., 2001; Steffensen et al., 1999). The number of spin-outs from U.S. universities are found to be positively associated with a university's intellectual eminence and its licensing policies, particularly with regard to making equity investments in start-ups (Di Gregorio and Shane, 2003). Also, the business development capabilities of a university's technology transfer office, which rely mainly on the quality of its staff and clearly defined processes, are found to augment the number of spin-out companies created (Lockett and Wright, 2005). Moreover, benefits for and effects on academia are investigated. A study of Bray and Lee (2000) shows, for example, that holding equity in university spin-offs creates, on average, a ten times higher income for U.S. universities than licensing.

On the micro level, characteristics and performance of academic spin-offs (Walter et al., 2006; Müller, 2006) are examined. Besides employment growth, turnover growth, and fund raising (especially venture capital funding), survival is frequently examined. The patent stock at founding as well as the patent scope, for example, significantly increases an academic spin-off's probability of survival (Shane and Stuart, 2002; Nerkar and Shane, 2003).

Rothaermel and Thursby (2005b) find that the number of backward patent citations increases the total amount of funds raised, increases the probability of venture capital financing, and lowers the firm's probability of failure. Moreover, strong university linkages of spin-offs located in an incubator to the incubator-sponsoring university reduce the probability of failure but retard timely graduation as well (Rothaermel and Thursby, 2005a). Concerning fund raising, European academic spin-offs are found to start with a larger amount of capital if there has been a formal transfer of technology from the university to the spin-off in terms of a patent transfer or an exclusive license agreement. However, those spin-offs have not outperformed spin-offs without formal technology transfer in raising second round financing (Clarysse et al., 2007).

In some studies, characteristics and performance measures of spin-offs are compared to those of non-academic start-ups. Egeln et al. (2003b) find that employment in the year of establishment is higher in academic spin-offs than in other ventures. Furthermore, employment growth of academic spin-offs in the first years after the establishment is considerably higher than the employment growth of other new ventures. Dahlstrand (1997) finds that, after an initial ten-year period, spin-offs grow significantly faster than other start-ups. But the evidence is mixed: Ensley and Hmieleski (2005) show that university-based start-ups perform significantly worse than their independent counterparts in terms of revenue growth and cash flow. Similarly, Egeln et al. (2007) detect that Austrian academic spin-offs have higher probabilities of surviving but do not perform better in terms of employment or turnover growth.

The location decision of academic spin-offs was investigated in detail by Egeln et al. (2004). The theory suggests that in order to benefit from knowledge-spillover effects spin-offs should locate close to their incubator institution. Egeln et al. (2004) find instead that proximity to incubators is not important for the location decisions of German academic spin-offs.

Time is a rather disregarded factor in the literature of technology transfer, especially in the spin-off literature. Markman et al. (2005) explicitly focus on the time factor. They investigate the determinants and effects of innovation speed in university licensing measured as the time which elapsed between the disclosure of an invention and the licensing of the same.

Very few studies give some hints about the impact of being still employed in university after founding a company on firm performance, but they are based on very small sample sizes of eight to twelve spin-offs (Olofsson and Wahlbin, 1984; Doutriaux, 1987). To the best of my knowledge, there are no studies which have investigated the determinants of the duration of the time period that elapses after the founders have left university.

2.3 Determinants of academic spin-off's transfer speed

As technology transfer by means of establishing a company is a complex process with different stages, there may be several factors influencing the time that elapses between leaving university and the establishment of a spin-off.

The following section discusses the impact of complementarities in skills, the nature of knowledge transferred, the founders' academic status, the motivations to start the firm, and support from academic institutions on academic spin-off's transfer speed.

2.3.1 Complementarities in skills

Theoretical explanations on why some founders of academic spin-offs established their firm later than others can be borrowed from the theory developed by Lazear (2004) who explains which people are more likely to establish a business. Lazear's theoretical model states that an entrepreneur has to be jack-of-all-trades. This means that an entrepreneur is less specialized and more a generalist because an entrepreneur must have, at least on a basic level, some knowledge of a wide variety of business areas. Hence, people who tend to become entrepreneurs should have a particular strategy on how to invest in their own human capital. Those whose initial skill endowment is unbalanced should invest in skills in which they are weak. Even those with balanced skills will invest in their skills if the prospective gain in income exceeds the marginal costs. In other words, Lazear's theory is about complementarities in skills which are especially relevant for entrepreneurs.

If complementarities actually exist, for example, between engineering and management skills, founders have to acquire a whole set of competencies or search for other specialized team members. A scientist with an unbalanced skill profile has to first acquire complementary skills, such as management skills, before the establishment of her own venture becomes worthwhile. This is time-consuming and affects the period of time between the drop-out of academia and the point in time when the venture is established. After leaving a public research institution, scientists with a balanced skill profile will therefore venture more quickly than scientists with an unbalanced skill profile. Thus, spin-offs are expected to exhibit shorter time-lags if the founders hold certain combinations of academic subjects.

Since it is very time-consuming to accumulate missing knowledge, such as management skills, professional experience in the private sector of the economy, or industry-specific experience, an appropriate alternative can be to get one or more other persons on board and establish the firm together. Apart from pooling of skills via team formation, teams are usually found to be more successful in raising external capital (Wright et al., 2007). Furthermore, start-up financing usually relies strongly on founders' private

wealth. Team formation is thus a pooling of at least two resources which are essential for starting a business: skills and funds. Upon this reasoning, spin-offs established in teams are expected to have shorter time-lags between the drop out of academia and the firm formation.
On the other hand, there are reasons why to expect that teams might rather exhibit longer time-lags. The team members might not know each other beforehand. It takes time to find each other, get in touch, and to agree on the course of action.

2.3.2 The nature of knowledge transferred from academia and founders' academic status

In their typology of university spin-offs, Pirnay et al. (2003) proposed to distinguish spin-offs by two dimensions: the nature of knowledge transferred from university and the academic status of individuals involved in the new business venturing process.

The nature of knowledge transferred from academia

Concerning the technology or the knowledge they transfer, academic spin-offs are quite heterogeneous. In the empirical analysis, I will distinguish between three types of knowledge which is transferred from academia: research results, newly developed scientific methods, and specific skills acquired at the public research institute. These types differ primarily in their specificity of knowledge. While new research results usually have a quite narrow application range for commercial exploitation, the scope is wider for methods and widest for competencies acquired in academia.

Three types of spin-offs can be distinguished along these elements which differ in their level of technology transfer.

Research-transfer spin-offs: New *research results* developed by at least one of the founders must have been *indispensable* to the creation of the firm (high-level technology transfer).

Method-transfer spin-offs: New *scientific methods*, which at least one of the founders acquired during the time at the public research institute, must have been *indispensable* to the creation of the firm (medium-level technology transfer).

Competence spin-offs: *Specific skills*, which at least one of the founders acquired during the time at the public research institute, must have been *indispensable* to the creation of the firm (low-level technology transfer).

It is reasonable to assume that the time which elapses after leaving university is highly influenced by the type of technology transfer. If the establishment is based on new research findings, a spin-off should be founded closer to the time of leaving academia than if the establishment is based on specific skills acquired at university. The finding of new research results usually opens a *"window of opportunity"* during which the opportunity has to be exploited before the window is "closed" by competitors. Since usually not a single researcher, but researchers and research teams in different institutions (both academia and commercial enterprises) engage in similar projects, the window of opportunity for commercialization of research results might be rather small. Additionally, I expect the outcome of most technological research projects to have an area of application which is relatively clear. Thus, opportunity recognition should not take too much time. On the other hand, if research results are protected by intellectual property rights owned by the university, start-up might be retarded due to legal processes and time-consuming negotiations.

The application range for newly developed methods is wider than for research results. Therefore, more time might pass before a marketable product or service is developed. Since skills are not easily transferable across individuals and can be hardly copied by others, the window of opportunity will be open much longer for the exploitation of individual skills than for successful exploitation of research results or newly developed methods. Furthermore, opportunity recognition might need much more time and industry experience before a promising business idea or market gap opens up.

To sum up the arguments, the time factor is of high relevance when research results are sought to be transferred to marketable products. Its relevance is lower for the commercialization of newly developed methods and lowest for the commercialization of academic skills. These effects can be partly allayed by the fact that with regard to the transfer of intellectual property rights the time-lag should be longer for research-transfer spin-offs than for competence spin-offs. Indeed, since there was no Bayh-Dole type of Act in Germany before 2002, this effect may be negligible in this analysis.[2]

[2]Before the abolishment of the "professor's privilege" in 2002 not the university but the academic inventors were assigned the property rights of their inventions.

Founders' academic status

The second dimension in which academic spin-offs differ is the academic status of the individuals involved in the business venturing process. According to Pirnay et al. (2003), a distinction between spin-offs initiated by researchers and spin-offs initiated by graduates appears to be appropriate. First of all, start-ups of graduates should exhibit longer time-lags than start-ups of researchers for the simple reason that they lack experience at the moment of graduation. Furthermore, establishing a business often does not necessarily comes along with the leave of university researchers. Presumably, when opportunity recognition happens during the time in academia, it is more common for researchers to maintain their position in academia, at least on a part-time basis, while most of the students will either quit their studies or wait with firm formation until graduation.

2.3.3 Motivations to start the firm and support from academic institutions

Usually, there is a large variety of motivations behind setting up a firm. Different motivations and aspirations for the foundation of a company apply to founders of academic spin-offs. It is reasonable to believe that some motives accelerate both opportunity recognition and organizational processes in the pre-seed phase. People who are mainly driven by the desire to work self-determined, i.e. to be their own boss, might have had the wish to become self-employed at the back of their mind long before. Therefore, they are expected to recognize faster whether skills they acquire, methods they develop, or research they conduct can be exploited commercially. For this reason, different start-up motives are included in the analysis and their influence on transfer speed is investigated in an explorative nature.

Other potential factors influencing the time between leaving university and the firm formation are various kinds of support provided by the academic institution. Support ranges from courses, infrastructure as wells as legal and business advice to the setting up of contacts and support from colleagues. This assistance may help to overcome founding obstacles such as the lack of capital, insufficient economic and commercial skills, and dealing with permit procedures, laws and provisions. Spin-offs which have made use of start-up assistance from their academic institution should thus have shorter time-lags.

2.4 Empirical analysis

2.4.1 The econometric models

In this section, I will discuss two different approaches and their adequacy for analyzing the period of time between the drop-out of academia and firm formation. The time-lag can both take negative and positive values. For example, a founder who has left university in 1998 and has established his firm in 2000 is assigned a time-lag of +2 years. If the founder has left university in 1998 and has already established his business in 1996, the founder's corresponding time-lag is −2 years. Due to the nature of the survey design, some negative time-lags are left-censored. For founders who had established their business, e.g. in 2000, and had still been in academia when the survey was conducted (end of 2001), it is known that the time-lag is negative. We further know, since the founder will stay in academia at least until 2002, that the time-lag is equal or less than −2 years. Consequently, simple regression techniques as ordinary least squares (OLS) yields inconsistent estimates. In the following, I will present and compare two estimation models which aim to account for the specific structure of the data, the *censored-normal regression model* and the *Cox regression model.*

Cox regression model

In order to analyze the time to the occurrence of an event, it is appropriate to deviate from the normality assumption and use techniques of survival analysis. To estimate the effect of certain covariates $\mathbf{x}_i$ on the hazard rate $h(t|\mathbf{x}_i)$, which is the instantaneous rate of failure[3] at a given time t or the age specific failure-rate, most commonly proportional hazard models, expressed by

$$h(t|\mathbf{x}) = h_0(t)\exp(\boldsymbol{x}'\boldsymbol{\beta}),$$

are used.

[3]The risk of failure is the risk of the occurrence of the event under investigation, i.e. here the "risk" of establishing the spin-off.

As the baseline hazard $h_0(t)$[4] is time-dependent, but not influenced by the covariates, each individual (firm) faces the same baseline hazard. Because of that, comparing subject i to subject m, one obtains from the model

$$\frac{h(t|\mathbf{x}_i)}{h(t|\mathbf{x}_m)} = \frac{\exp(\boldsymbol{x}_i'\boldsymbol{\beta})}{\exp(\boldsymbol{x}_m'\boldsymbol{\beta})},$$

which is called hazard ratio. The hazard ratio is constant, assuming that the covariates $\boldsymbol{x}_i$ and $\boldsymbol{x}_m$ do not change over time.

From the formulation of the hazard rate it is easy to see that for a binary covariate x_k shifting from zero to one the hazard ratio is

$$\frac{h(t|\mathbf{x}_i, x_k = 1)}{h(t|\mathbf{x}_i, x_k = 0)} = \frac{\exp(\boldsymbol{x}_i'\boldsymbol{\beta} + 1 \cdot \beta_k)}{\exp(\boldsymbol{x}_i'\boldsymbol{\beta})} = \exp(\beta_k),$$

which gives the coefficients an easy interpretation. As a semi-parametric estimation method proposed by Cox (1972) imposes no restrictions on the shape of the baseline hazard and therefore allows the baseline hazard to be as flexible as possible, Cox regression is used for the analysis.

Since more than one observation is observed to fail at the same time, the analysis has to take *tied failures* into account. Basically, there are two approaches how to deal with tied failures: the marginal calculation and the partial calculation. The marginal calculation assumes that tied failures arise from imprecise measurement, i.e. the observations do not have exactly the same failure time. On the other hand, the partial calculation assumes a discrete-time model, i.e. it assumes that the event under investigation really occurs at the same point in time. Both approaches are computationally very intensive. This is especially true if many ties exist. In practice, it has become common to use approximations instead (Breslow, 1974; Efron, 1977). Since the time from leaving university to venture is measured in years, one can easily see that tied failures should be due to imprecise measurement and the marginal calculation is preferred. Efron's approximation is more accurate than Breslow's method of handling ties. Therefore, Cox regressions are calculated using Efron's approximation.

One major drawback using survival analysis is that the time under investigation is not allowed to take negative or zero values. Additionally, for those founders who were

[4]The baseline hazard is the hazard rate of observations with zero covariates. The covariates shift the baseline hazard multiplicatively.

still in academia when the survey was conducted, one just knows that the time value is negative. The exact value of these negative time-lags is not known. Therefore, no difference is made between spin-off establishments which are founded in the time when the founder was still in academia. These observations are assumed to enter and "fail" immediately and a time value of 0.1 was assigned to them. Similarly, all firms whose founders left academia in the year of establishment (original time value of zero) got a new time-value of 0.2. For all other observations (these with a positive time-lag), the time-lag was measured in years. This procedure is possible because the Cox proportional hazards model is sensitive only to the order of the failure events. Thus, as long as one keeps the earliest failure events as occurring first, the results will remain unchanged (Gould, 1999). The robustness of this procedure is tested and approved by different transformations of the time under investigation which all yield exactly the same results in the Cox regression.[5] Nevertheless, applying this procedure results in a partial information loss concerning all start-ups with negative time-lags.

Tests based on Schoenfeld residuals (Schoenfeld, 1982; Grambsch and Therneau, 1994) reveal a violation of the proportional hazard assumption concerning the covariates *method-transfer spin-off* and *graduate*. Therefore, another model (model B) is estimated with the same specification as in the original model (model A) but stratified by the variables *method-transfer spin-off* and *graduate*. In contrast to the standard Cox model, which assumes proportional hazards for each explanatory variable, a stratified model makes it possible to control for the effect of a certain variable without assuming proportional hazards for that variable (Parmar and Machin, 2006). Stratification allows for different baseline hazards for each of the possible categories[6] but constrains the coefficients to be the same. The model is now relaxed in favour of

$$h(t|\boldsymbol{x}_i) = h_{0j}(t)exp(\boldsymbol{x}_i^{'}\boldsymbol{\beta}), \qquad \text{if } i \text{ is in group } j, \;\; j = 1, 2, 3, 4.$$

Tests on the proportional hazard assumption do not reveal further violations. Because the analysis in model B is stratified by the variables *method-transfer spin-off* and *graduate*, the effect of these variables is absorbed by the different shapes of the baseline hazard and no coefficients are estimated.

[5] Details on the transformation can be found in the Appendix 2.A3.

[6] Because *graduate* and *method-transfer spin-off* are binary, four combinations appear and the model allows four different baseline hazards.

2.4.1.1 Censored-normal regression

Another estimation model to be taken into account for analyzing the duration from the drop-out of academia and establishing the firm is censored-normal regression, a generalization of the Tobit-model (Tobin, 1958; Amemiya, 1973, 1984). Censored regression models account for the fact that for some observations, the "true" value is not known. One refers to those observations as *censored* observations. For censored observations, the value of the variable is only known to be smaller (left-censoring) or larger (right-censoring) than a certain threshold. The central feature of censored-normal regression is that rather than having fixed points for the left-censoring and the right-censoring limit as in the Tobit-model, the censoring value is allowed to differ from one observation to another.

As described above, the period of time between leaving academia and founding a firm is left-censored with individual limits L_i for those firms the founders of which had still been in academia when the survey was conducted. The model then is

$$y_i^* \;=\; \boldsymbol{x}_i'\boldsymbol{\beta} + u_i \qquad u_i \sim \mathcal{N}(0, \sigma^2),$$

with y_i^* being the latent dependent variable. The observed dependent variable is denoted by y_i

$$y_i \;=\; \begin{cases} L_i & \text{if} \quad y_i^* \leq L_i, \\ y_i^* & \text{if} \quad y_i^* > L_i. \end{cases}$$

The parameters $\boldsymbol{\beta}$ and σ are estimated using maximum likelihood estimation. The log-likelihood function to be maximized with respect to $\boldsymbol{\beta}$ and σ is given by

$$ln\ L \;=\; \sum_{y_i = L_i} ln \left\{ \Phi\left(\frac{L_i - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma} \right) \right\} + \sum_{y_i = y_i^*} \left\{ \frac{1}{\sigma} \phi\left(\frac{y_i - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma} \right) \right\} \;,$$

where $\Phi()$ denotes the cumulative standard normal distribution, and $\phi()$ denotes the standard normal density.

The results can be interpreted as in standard OLS regression (Wooldridge, 2002b). Since all determinants of the founding time-lag are represented by dummy variables, β_k depicts the effect for discrete change of the dummy variable x_k from zero to one.

2.4.1.2 Censored-normal regression vs. Cox regression

Both the censored-normal regression and the Cox regression have been widely used in duration analyses. Since each of the model has its own advantages, the determinants of university spin-off's transfer speed are estimated using the two estimation models. Censored-normal regression is adopted because it can deal with left-censored and even with negative variables. No data transformation procedures have to be applied in order to use this estimation method. Therefore, a partial loss of information is avoided when using censored normal regression. Using censored normal regression, we are not faced with the problem of tied failures, too. Furthermore, the estimation results can be interpreted much more easily. The coefficients of the censored regression model give a clear picture about the size of the effect while the meaning of an increase in the hazard rate is more difficult to understand. On the other hand, censored normal regression strongly relies on the assumption that the distribution of the error terms is normal. However, no distributional assumption is made to obtain estimates from Cox regression.

2.4.2 Database and descriptive statistics

For the following empirical analysis, a survey of more than 20,000 German start-ups operating in research- and knowledge-intensive industries and which were founded in the years 1991 to 2000 is used as data set. In the end of 2001 a computer-assisted telephone survey was conducted in order to both estimate the number of academic spin-offs in Germany and to identify their core characteristics.

The underlying population from which a stratified random sample was drawn consists of all new ventures in the research- and knowledge-intensive industries[7] which were

[7]Research- and knowledge-intensive industries include cutting edge technology (e.g. manufacturing of pharmaceutical products), high-technology (e.g. manufacturing of chemicals), technology-intensive services (e.g. telecommunications) and knowledge-intensive services (e.g. business consulting). A classification based on NACE codes is provided in Table 2.A2. Other industries are excluded since it is assumed that only a small fraction of academic spin-offs is founded in those industries.

established between 1996 and 2000.[8] Stratification criteria are the industry, the year of establishment, and the type of region where the start-up was established. Data concerning all start-up companies in Germany could have been retrieved from the Mannheim Enterprise Panel which is built upon firm level data made available by Creditreform.[9] One major advantage of that survey is the way academic spin-offs are identified. Instead of asking technology transfer offices about spin-off activity at their research institutions, founders themselves were asked about their academic background and the role of technology transfer for establishing their business. Technology transfer offices and heads of institutions might have limited information about the total amount of spin-off activities from their institutions. First, they lack information about the characteristics of the founder or the start-ups. Second, information about spin-offs which have been established years after the founders have left university will be hardly available for the institutions.

During the interview each start-up was asked about the academic background of the founders and the relevance of academic skills, new scientific methods, and results of the founders' own research activities in the establishment process. Academic spin-offs are firm foundations of persons with an academic background (students, graduates, and researches) who classified academic skills, newly developed methods, or own research results as *indispensable* for the establishment of their firm. A similar approach was used by Mansfield (1995) to identify technology transfer from academic research concerning the development of new products and processes in mature firms.

For each academic spin-off, information on the name of the academic institution at which the founders had studied or worked, the time when the last founder left this institution, and the academic disciplines were obtained. Furthermore, general facts about the firm (e.g. start-up size, turnover, employment, R&D activities) were retrieved during the interview.

Using the above described methodology, out of the total number of start-ups surveyed (20,241), 1,810 spin-offs have been identified and the time until establishment took place can be analyzed. Out of these 1,810 academic spin-offs, 15 percent are research-transfer

[8]During the interview, the founders where asked about the year they started the firm. I assume that year to be the more precise information about the year of establishment. Therefore, some firms included in the analysis are assigned years before 1996 and after 2000 as year of foundation.

[9]Creditreform is Germany's major credit rating agency. It collects information about almost all German firms for the purpose of providing information about a firm's financial standing (more detailed information on the Mannheim Enterprise Panel is provided by Almus et al. (2000)).

spin-offs, 23 percent are method-transfer spin-offs, and 62 percent are competence spin-offs.

For all spin-offs the founders of which had, up to the time of the survey, already left the public research institute, a kernel density estimation of the time which elapsed between leaving academia and the establishment of the spin-off is calculated using the Epanechnikov kernel function. The corresponding graph of the kernel density estimation and a histogram of the time-lag is displayed in Figure 2.1. The time can take a negative value if at least one of the founders had still been active in academia after the venture was established. The univariate kernel density estimation shows that the distribution of the time to venture is positively skewed. Although the maximum of the density function is roughly around zero, a high density of time-lags of over 5 years signals that spin-offs established more than 5 years after quitting public research are rather probable. One can also see that even time-lags beyond 10 years are quite frequent.

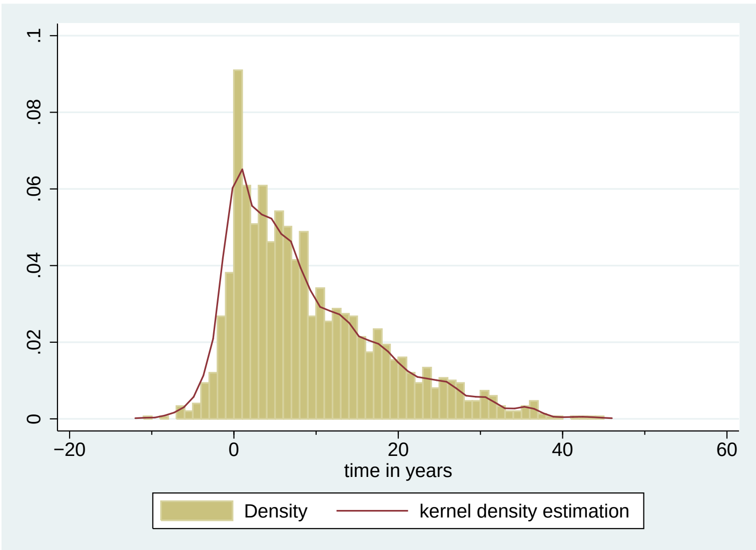


Figure 2.1: Histogram and kernel density estimation of the time to venture

Source: ZEW Spin-Off Survey 2001, author's calculactions.

Knowledge transfer via spin-off establishment is therefore not restricted to those who establish their firm directly after leaving university. Even many years after leaving a public research institute, knowledge and technology transfer may still take place.

Furthermore, descriptive statistics about the time-lag between leaving university and the spin-off establishment are shown in Table 2.1. Only about 33 percent of all spin-offs have been established with a time-lag below one year, as one can conclude from the fourth column. For ventures founded one year or more after the founder has left university, the period of time which elapsed in between was, on average, around 11 years. The finding of those sizable time-lags is in line with findings for engineering and technology start-ups in the U.S. For those start-ups, an average time-lag of 16 years between the completion of terminal education and company founding is observed (Wadhwa et al., 2008).

Table 2.1: Time-lag between leaving university and establishing a spin-off

	Type of spin-off			
Time-lag	research-transfer spin-off	method-transfer spin-off	competence spin-off	all
Founder(s) still in science	41%^{A,B}	28%^{B,C}	21%^{A,C}	25%
Established in the year after leaving	10%^{A}	10%^{C}	6%^{A,C}	8%
Mean (median) time-lag for positive time-lags	10.1 (7)	10.3 (7)	11.2 (9)	10.9 (8)

Notes: Median in parentheses; *A:* significant differences between research-transfer spin-offs and competence spin-offs, *B:* significant differences between research-transfer spin-offs and method-transfer spin-offs, *C:* significant differences between method-transfer spin-offs and competence spin-offs.

Source: ZEW Spin-Off Survey 2001, author's calculations.

Moreover, the descriptive statistics reveal substantial differences in the founding time-lag between the three types of spin-offs. Compared to spin-off with lower-level technology transfer, spin-offs with high-level technology transfer are established closer to the year the public research institution was left.

In order to test the effect of complementarities in skills, a dummy variable which indicates if a spin-off was established by a team of founders and a set of dummy variables which display the combination of subjects the founders studied[10] were included in the estimations. The founders studied mostly one single subject (76 percent). Subject

[10] These are different aspects as one founder could have studied several subjects or a team of founders could have studied the same subjects.

combinations are divided into four categories: a combination of natural science and engineering, a combination of natural science and business, a combination of engineering and business, and other combinations. With a fraction of about 13 percent, other combinations are the most frequent category. The corresponding fractions of the other categories - classified by the spin-off type - can be inferred from Table 2.2, in which descriptive statistics of all variables included in the econometric analysis are presented. Even if a spinoff was not established by a team of founders, the founder could have studied various subjects. In fact, 4 percent of all single founders show a combination of subjects. The other way around, team foundations do not necessarily show a combination of different subjects.

Table 2.2: Descriptive statistics

	Type of spin-off			
Variable	research-transfer spin-off	method-transfer spin-off	competence spin-off	all
Team	57%	58%	61%	60%
Academic subjects				
Nat & engin	4%	4%	4%	4%
Nat & business	5%	5%	4%	5%
Engin & business	$1\%^{B}$	$4\%^{B}$	3%	3%
Other combination	11%	$11\%^{C}$	$14\%^{C}$	13%
Single subject	78%	77%	75%	76%
Graduate	$35\%^{A,B}$	$64\%^{B,C}$	$75\%^{A,C}$	66%
Motivations to start the firm				
Economic potentials	$55\%^{A,B}$	$31\%^{B,C}$	$17\%^{A,C}$	26%
Self-determined working	$88\%^{A,B}$	$93\%^{B}$	$93\%^{A}$	92%
Income	60%	66%	65%	64%
Career	$24\%^{A,B}$	$13\%^{B,C}$	$9\%^{A,C}$	12%
Demand	50%	51%	48%	49%
Received support from academic institutions				
Courses	6%	$8\%^{C}$	$5\%^{C}$	6%
Infrastructure	$12\%^{A,B}$	$5\%^{B}$	$3\%^{A}$	5%
Advisory	5%	5%	3%	4%

Continued on next page...

Table 2.2 – Continued

Variable	*Type of spin-off*: research-transfer spin-off	method-transfer spin-off	competence spin-off	all
Contacts	10%^{A}	7%	5%^{A}	6%
Colleagues	26%^{A,B}	16%^{B,C}	10%^{A,C}	14%
Industry				
Cutting edge technology	13%^{A,B}	4%^{B,C}	6%^{A,C}	7%
High-technology	7%	4%	5%	5%
Other manufacturing	7%	5%	5%	5%
Software	9%	9%	8%	8%
Techn.-int. serv.	34%	40%	38%	38%
Knowledge-int. serv.	30%^{A,B}	38%^{B}	38%^{A}	37%
Eastern Germany	21%	21%	18%	19%
Year of foundation				
1990	1%^{B}	4%^{B}	2%	2%
1991	3%	2%	2%	2%
1992	3%	1%	2%	2%
1993	3%	3%	2%	3%
1994	2%	2%	3%	3%
1995	6%	6%	5%	6%
1996	14%	14%	13%	13%
1997	16%	12%^{C}	17%^{C}	16%
1998	14%	17%	17%	16%
1999	19%	17%	18%	18%
2000	17%	18%^{C}	15%^{C}	16%
2001	3%	3%	4%	3%

Notes: A: significant differences between research-transfer spin-offs and competence spin-offs, *B:* significant differences between research-transfer spin-offs and method-transfer spin-offs, *C:* significant differences between method-transfer spin-offs and competence spin-offs.

Cutting edge technologies (high-technologies) are those sectors defined by Grupp and Legler (2000) after 4-digit NACE classification in which the average R&D intensity is above 8% (3.5%-8%).

Source: ZEW Spin-Off Survey 2001, author's calculations.

The conjecture concerning the nature of knowledge transferred from academia and the time-lag was tested by differentiating between the three spin-off types introduced in section 2.3.2. Founders' academic status was measured as follows. If none of the founders has ever been a researcher the spin-off is called graduate spin-off. While 35 percent of research-transfer spin-offs have been founded by persons who have never been employed at a public research institution, the fraction for method-transfer spin-offs and competence spin-offs is much higher (64 percent and 75 percent respectively).

Five different motivations to start a firm can be distinguished while it is possible that multiple motivations apply to the founders' decision to start the firm. Founders can be driven by the economic potentials provided by research results, by the motivation to work independently and self-determined, by the motivation to improve one's personal income prospectives, by better career options than in academia, and by a specific corporate demand for products or services. Statistically significant differences between research-transfer spin-offs and competence spin-offs appear for the motivation to exploit economic potentials provided by research results and for the motivation to achieve better career options than in academia.

Spin-offs might have received support from their academic institutions prior to firm formation. Around 6 percent made use of courses and teaching events relevant for the founding process while 4 percent received individual legal or business advice. Provision of infrastructure (offices, secretarial service, access to laboratories etc.), establishment of contacts, and encouragement and support from colleagues was used more frequently by research-transfer spin-offs (high-level technology transfer) than by the spin-off types of lower-level technology transfer. These differences can be explained by a selection process of the supporting university. High-potential start-up ideas might have been supported preferentially.

In order to control for industry effects, research- and knowledge-intensive industries are subclassified into six industries: the cutting edge technology industry, the high-technology industry, the software industry, technology-intensive services, knowledge-intensive services and other manufacturing industries. The majority of the firms operates in technology-intensive services (38 percent), closely followed by firms operating in knowledge-intensive services (37 percent). Altogether, 7 percent operate in cutting edge technologies while the fraction of research-transfer spin-offs operating in cutting edge technology is almost twice as high (13 percent).

Another control variable (eastern Germany) is included in the analysis in order to account for differences in the time-lag due to German history. Before 1990, Germany was divided into the Federal Republic of Germany (FRG) and the German Democratic Republic (GDR). While the western part of Germany (FRG) has been a market economy since its foundation in 1949, the eastern part (GDR) was a centrally planned economy in a socialistic system. Therefore, it was not possible for people in the eastern part of Germany to establish a firm before the German reunification took place in 1990 when whole Germany became a market economy. Since most of the firms in the data set are established in the late 1990s, longer time-lags of spin-offs located in eastern Germany might be partly caused by the fact that firm formations could not have taken place in the socialistic system of the GDR.

Dummy variables capturing the year of establishment are included as further control variables. On the one hand, the dummies should capture effects of business cycles on academic spin-offs transfer speed. On the other hand, one has to account for the year of establishment because of the specific survey design described above.

2.4.3 Estimation results and discussion

Estimation results of the censored normal regression (model 1) and the Cox regressions (model 2a and 2b) are summarized in Table 2.3. Coefficients and standard errors are presented. Except for the foundation year for which "founded in 1990" is used as reference category, the categories with the highest fraction are used as reference category (single academic subject profile, competence spin-off, technological services). The first column presents the results of censored normal regression. The results of the unstratified and stratified Cox regressions can be found in the second and third column, respectively. Between the two Cox regression models (model 2a and model 2b) the coefficients considerably change neither in magnitude nor in significance. This indicates that the violation of the proportional hazard assumption in model A was not severe.

Overall, the hypotheses concerning complementarities in skills, stated in section 2.3, can be supported by the data. For spin-offs founded by a team of entrepreneurs, the time-lag is found to be two years less on average. This finding is supported by the results of the Cox regressions. The hazard ration for the team dummy is $\exp(0.241) = 1.27$ (see model 2b). This means that the hazard increases by 27 percent if the spin-off is founded by a team of founders. Hence, the time-lag is considerably shorter for spin-offs established by a team of founders. In addition to acquiring complementary skills by team formation, the positive effect of teams on transfer speed can be explained by pooling of financial resources and risk-sharing among the team members. Both pooling of financial resources and risk-sharing among the team members reduces the risk faced by the individual founder.

Table 2.3: Cox regression on the time-lag

	Censored-normal regression Model 1		Cox regression Model 2a		Model 2b	
	coeff.	se	coeff.	se	coeff.	se
Team	-2.044***	(0.537)	0.231***	(0.054)	0.241***	(0.054)
Subjects/Disciplines(1)						
Nat & engin	-1.995*	(1.153)	0.277**	(0.130)	0.255*	(0.131)
Nat & business	-2.295**	(1.132)	0.236**	(0.117)	0.230*	(0.117)
Engin & business	2.884**	(1.455)	-0.274*	(0.150)	-0.247	(0.153)
Other combination	-1.269	(0.781)	0.051	(0.077)	0.075	(0.077)
Research spin-off(2)	-2.086***	(0.779)	0.201***	(0.073)	0.165**	(0.074)
Method spin-off(2)	-1.254**	(0.602)	0.097	(0.060)	–	–
Graduate	5.734***	(0.690)	-0.513***	(0.064)	–	–
Motivations						
Economic potential	-1.704***	(0.610)	0.146**	(0.060)	0.149**	(0.060)
Self-determ. work.	-2.763***	(0.968)	0.266***	(0.092)	0.251***	(0.092)
Income	0.043	(0.499)	-0.034	(0.051)	-0.024	(0.050)
Career	-0.292	(0.895)	0.017	(0.086)	0.030	(0.086)
Demand	-0.343	(0.483)	0.004	(0.048)	0.000	(0.048)
Support						
Courses	-1.296	(0.894)	0.173	(0.108)	0.150	(0.108)
Infrastructure	-4.218***	(1.103)	0.508***	(0.125)	0.433***	(0.125)
Advisory	-0.441	(1.237)	0.098	(0.126)	0.052	(0.126)
Contacts	1.633	(1.040)	-0.154	(0.110)	-0.139	(0.109)
Colleagues	-3.976***	(0.693)	0.525***	(0.078)	0.494***	(0.078)
Industry(3)						
Cutting edge techn.	1.540	(1.055)	-0.172*	(0.103)	-0.181*	(0.103)
High-technology	2.862**	(1.155)	-0.283**	(0.112)	-0.298***	(0.112)
Other manufact.	5.343***	(1.132)	-0.471***	(0.110)	-0.477***	(0.111)
Software	-3.293***	(0.861)	0.391***	(0.093)	0.376***	(0.093)
Knowl.-inten. serv.	1.134**	(0.566)	-0.105*	(0.056)	-0.109*	(0.057)
Eastern Germany	1.780***	(0.621)	-0.134**	(0.062)	-0.142**	(0.062)
Year of foundation(4)						
Founded in 1991	-0.096	(1.855)	0.148	(0.223)	0.048	(0.223)
Founded in 1992	0.668	(2.122)	0.014	(0.236)	-0.092	(0.236)
Founded in 1993	2.534	(2.002)	-0.252	(0.214)	-0.317	(0.216)
Founded in 1994	0.834	(2.049)	-0.048	(0.217)	-0.128	(0.217)
Founded in 1995	2.925*	(1.704)	-0.230	(0.185)	-0.323*	(0.186)

Continued on next page...

Table 2.3 – Continued

	Censored-normal regression Model 1		Cox regression Model 2a		Model 2b	
	coeff.	se	coeff.	se	coeff.	se
Founded in 1996	1.271	(1.544)	-0.124	(0.168)	-0.193	(0.169)
Founded in 1997	1.883	(1.505)	-0.143	(0.167)	-0.228	(0.168)
Founded in 1998	2.365	(1.551)	-0.276*	(0.167)	-0.341**	(0.167)
Founded in 1999	2.502	(1.527)	-0.232	(0.166)	-0.319*	(0.167)
Founded in 2000	2.188	(1.548)	-0.214	(0.168)	-0.290*	(0.169)
Founded in 2001	4.379**	(2.001)	-0.376*	(0.203)	-0.495**	(0.204)
Constant	4.408**	(1.892)				
Observations	1810		1810		1810	
Left-censored obs.	315					
Log-likelihood	-5834		-11576		-9555	
χ^2			391		207	
Pseudo R^2	0.034					

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) competence spin-off, (2) single academic subject profile (3) technology-intensive services (4) founded in 1990. Interval censoring is accounted for using the Efron approximation.

Source: ZEW Spin-Off Survey 2001, author's calculations.

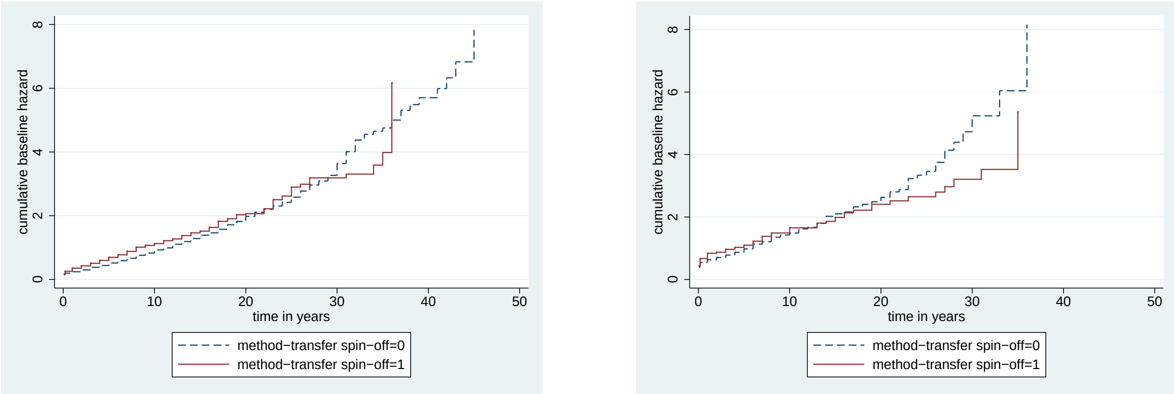
Significant negative effects of two of the subject combinations dummies in the censored regression model (and significant positive effects in the Cox regression models) show that the time-lag is around two years shorter for a combination of natural science with engineering or business than for a single subject profile of the founders. Also, these combinations have considerably higher hazards. Thus, the probability that, at any point in time, spin-offs are founded shortly after leaving public research is higher for these combinations than for no combinations of academic disciplines. These effects support the presumption that complementarities in skills are present and notably relevant in the establishment process of academic spin-offs.

On the contrary, in model 1 and model 2a, spin-offs combining an engineering and business administration background are found to be established with a longer time-lag than spin-offs with a single subject profile. This contrasts the hypothesis concerning skill complementarities and is rather surprising. Researchers and graduates in business administration may first and foremost carry out economic activities, e.g. consulting and marketing services, which do not require complementary skills from other fields. Additionally, researchers and graduates in engineering may have already acquired basic business skills as part of their academic studies since including such courses in the curricula is quite common in German engineering faculties. The longer time-lag for spin-offs combining both engineering and economic skills may thus be caused by higher search efforts in finding the partner from the other field. This does not have to apply to natural science since the commercialization of research results in natural science may both require additional technical skills for setting up production and economic skills for running the business and marketing the products. However, this effect is not found to be significantly different from zero in model 2b.

Furthermore, the spin-off type has a considerable influence on transfer speed. A research-transfer spin-off is established two years closer to the time in academia than competence spin-offs. The hazard estimated using the stratified Cox regression is 18 percent ($\exp(0.165)-1$) higher for research-transfer spin-offs than for competence spin-offs. This confirms the hypothesis that due to a small "window of opportunity" and faster opportunity recognition research-transfer spin-offs are established earlier than competence spin-offs. For method-transfer spin-offs, I find the time-lag to be about one year shorter than for competence spin-offs. However, the coefficient in the unstratified Cox regression model (model 2a) is not found to be significantly different from zero. In the stratified Cox model, the influence of the variable "method-transfer spin-off" is absorbed by the shape and position of the baseline hazard (see section 2.4.1). Comparing the cumulative baseline hazard (see Figure 2.2), it is found that for spin-offs founded by graduates (left) the cumulative baseline hazard of method-transfer spin-offs lies slightly above the cumulative baseline hazard of competence spin-offs if the time-lag is less than thirty years.[11] The picture is less clear for spin-offs set up by researchers (right). The cumulative baseline hazards are approximately the same for method-transfer spin-offs and competence spin-offs for time-lags less than fifteen years while for longer time-lags the cumulative baseline hazard of method-transfer spin-offs lies even below that of competence spin-offs.

The censored-normal regression model indicates (as well as the unstratified Cox regression) that the academic status of the founder (researcher or graduate) has a significant and rather large impact on transfer speed. Start-ups founded by graduates have time-lags which are about six years longer (and a hazard which is about 40 percent lower) than start-ups set up by researchers. This result is quite intuitive as graduates, which have never worked as researchers, are younger and lack research experience as well as professional experience. Hence, graduates must use market experience as a substi-

[11] If the cumulative baseline hazard for method-transfer spin-offs lies above the cumulative baseline hazard for competence spin-offs, method-transfer spin-offs are established with a shorter time-lag.



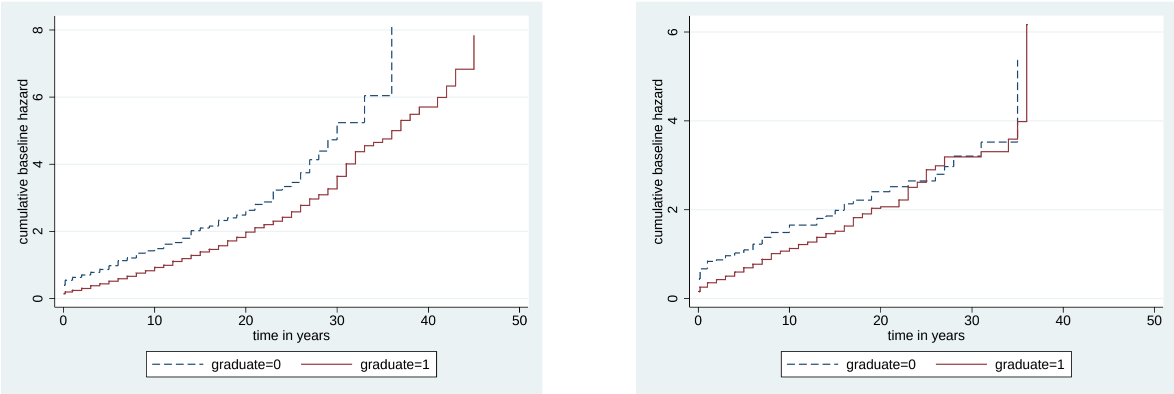
(a) Graduate = 1 (b) Graduate = 0

Figure 2.2: Cumulative baseline hazards by *graduate*

Source: ZEW Spin-Off Survey 2001, author's calculations.

tute for the experience a researcher has gained in academia. Although the stratified Cox regression cannot give a precise estimate of the magnitude of the effect of the academic status, a comparison of the estimated baseline hazards - as done for the variable "method-transfer spin-off" - supports the findings of model 1 and model 2a. The cumulative baseline hazard of researchers lies above the cumulative baseline hazard of start-ups which are established by graduates (see Figure 2.3), i.e. start-ups of researchers exhibit shorter time-lags at every point in time.

The coefficients of the variables capturing the effect of different start-up motivations reveal some further interesting insights. Among the potential motivations for spin-off establishments, the motive to work self-determined speeds up establishment considerably. The time-lag for founders driven by that motivation is about three years less. The higher hazards in model 2a and 2b for that type of motivation confirms this result. Likewise, the motivation to take promising economic opportunities provided by research results has a positive influence on technology transfer speed. The founders who were motivated by the economic potential provided by research results have higher hazards and establish their firm approximately two years earlier. This result accompanies the findings about the effects of the type of technology transfer. Other motivations are not found to show significant effects on academic spin-off's transfer speed.



(a) Method-transfer spin-off = 0 (b) Method-transfer spin-off = 1

Figure 2.3: Cumulative baseline hazards by *method-transfer spin-off*

Source: ZEW Spin-Off Survey 2001, author's calculations.

Concerning the support received from academic institutions prior to firm formation, the results of all models show a significant influence of infrastructure support and encouragement by colleagues and professors on transfer speed. While the provision of infrastructure reduces the time-lag substantially, the encouragement of colleagues is similarly important for the acceleration of technology transfer through academic spin-offs. Both the provision of infrastructure and encouragement of colleagues speed up firm formation by about four years.

These two kinds of university support differ materially. Positive effects from support of infrastructure on transfer speed are quite obvious since start-up costs are reduced substantially when existing infrastructure can be utilized at low or zero cost. The explanation for the rather large effect of encouragement of colleagues and professors is not that obvious. The results of the empirical analysis suggest that psychologic factors such as peer support and entrepreneurial climate are rather important in the start-up decision process.

First, encouragement of colleagues helps with the opportunity identification. Those who have never thought about being self-employed will need much more time to recognize that their research results or skills have the potential to be commercialized by the establishment of a new firm. The idea that their former scientific work provides the basis for a business idea might not become apparent until the researcher has gained some market experience. If the scientist gets in contact with some "spirit of entrepreneurship" during the time at university, this recognition process will be substantially accelerated. In this context, colleagues may act as guides.

Second, support from colleagues means professional assistance. Apart from the possible acceleration of the opportunity identification process, the founder knows that he can fall back on the knowledge of former colleagues on an informal basis.

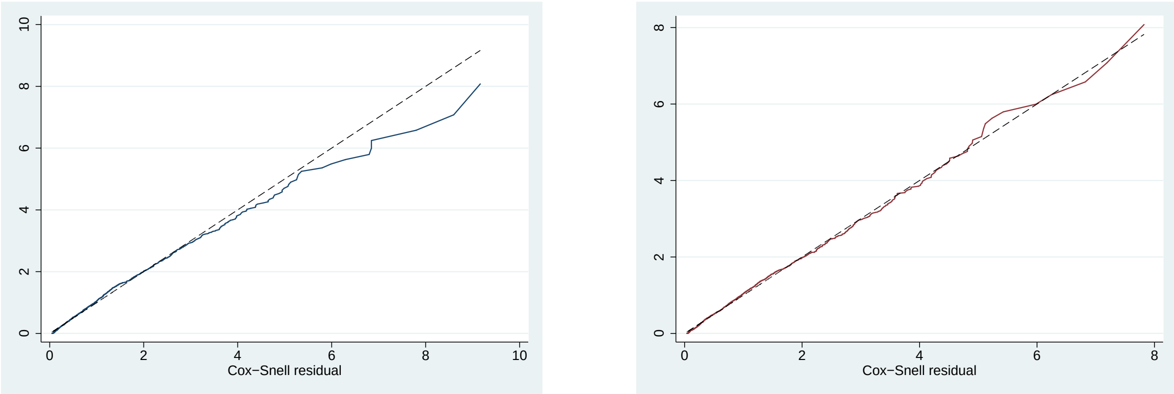
The causality of the variables measuring support from the academic institution should be interpreted with caution although support has been only considered if it was used prior to firm formation. However, founders who started their business years after having left university will find it quite difficult to use university infrastructure or to receive support from former colleagues.

As expected, the coefficient of the dummy variable "eastern Germany", which is included to account for the fact that it was not possible to establish a firm in the socialistic system of the GDR, is found to be significantly positive.

The industry dummies show that there are substantial differences in technology transfer speed between the sectors. Academic spin-offs operating in the software industry are established closest to the time being in academia. To understand this result, one has to remember that all spin-offs in the sample had been established between 1996 and 2000, the time of the "New Economy boom". During that time, it was rather easy for firms in information technologies, especially for software firms, to find an investor, receive funding, and acquire customers.

For the Cox regressions, an evaluation based on Cox-Snell residuals (Cox and Snell, 1968) was used as a goodness of fit measure. If a model which fit the data well, the Cox-Snell residuals ought to have a standard exponential distribution with a hazard function of one for all t. Accordingly, the cumulative hazard of the Cox-Snell residuals should form a straight 45 degree line. The cumulative hazard function of the Cox-Snell residuals is estimated using the Nelson-Aalen estimator. For both models a good fit could be observed, but the stratified model (model 2b) has a slightly better fit than the unstratified model (model 2a) (see Figure 2.4).

In order to test the robustness of the results, the model was also estimated using an ordered logit model (see appendix 2.A1) with five categories of the founding time-lag. The results of the ordered logit model confirms the results of the duration analysis.



(a) Model 2a

(b) Model 2b

Figure 2.4: Goodness of fit - Cox-regressions

Source: ZEW Spin-Off Survey 2001, author's calculations.

However, the evidence for a acceleration effect of a subject combination between natural science and business administration and a combination of natural science and engineering vanishes.

2.5 Conclusions

This chapter has focused on the phenomenon that a large amount of technology transfer by means of academic spin-off occurs years after researchers or graduates have left the academic institution - a fact which was in general known but ignored in the existing spin-off literature. This "late" technology and knowledge transfer is not unimportant. New academic research results, methods or skills obtained by founders in research- and knowledge-intensive industries have been indispensable for the creation of the spin-off even more than ten years after the institution was left. Policy makers should therefore not only concentrate on direct spin-off activity but also consider "late" technology transfer as an important channel of technology transfer in their own agendas.

The empirical analysis shows that complementarities in skills are likely to be present in the spin-off establishment process. This conclusion is drawn from both the fact that the time-lag of spin-off establishments in teams is shorter than the time-lag of single founders and from the positive effect of certain combinations of academic subjects on transfer speed. A good matching of founders with complementary skill profiles can thus foster academic spin-off creation. Policy makers as well as technology transfer offices should take that into account, for example, by offering assistance in the matching process.

Additionally, the type of technology transferred appears to have an important influence on the transfer process presumably due to a smaller "window of opportunity". Since the potentiality of imitation is larger for research-transfer spin-offs than for competence spin-offs, spin-offs with high-level technology transfer are established earlier than those with a lower-level knowledge transfer.

Spin-offs started by graduates are found to be established with a significant longer time-lag. Although numerous policy initiatives exist to promote academic start-ups, entrepreneurship is obviously not seen as a career option directly after completing one's studies. Future studies will help to show if the professional experience which may be accumulated during that time results in better firm performance.

The positive influence of support in terms of university infrastructure and encouragement from colleagues and professors on transfer speed give further suggestions to policy makers on how to encourage fast spin-off establishment. While more formal support in terms of providing infrastructure helps to speed up spin-off formation, peer support in terms of encouragement of colleagues and professors is a crucial factor as well.

2.A Appendix

2.A1 Regression results - Ordered logit

Table 2.4: Ordered logit model with 5 categories for the time-lag

	Ordered logit	
	coeff.	se
Team	-0.421***	(0.098)
Subjects/Disciplines[1]		
Nat & engin	-0.296	(0.233)
Nat & business	-0.279	(0.216)
Engin & business	0.583**	(0.271)
Other combination	-0.202	(0.139)
Research-transfer spin-off[2]	-0.417***	(0.139)
Method-transfer spin-off[2]	-0.349***	(0.108)
Graduate	1.066***	(0.122)
Motivations		
Economic potential	-0.310***	(0.111)
Self-determined working	-0.451***	(0.169)
Income	-0.019	(0.092)
Career	0.044	(0.161)
Demand	-0.083	(0.088)
Support		
Courses	-0.154	(0.187)
Infrastructure	-0.815***	(0.237)
Advisory	-0.134	(0.227)
Contacts	0.325	(0.199)
Colleagues	-0.763***	(0.138)
Industry[3]		
Cutting edge technology	0.382**	(0.189)
High technology	0.616***	(0.204)
Other manufacturing	1.011***	(0.212)
Software	-0.639***	(0.171)
Knowledge-intensive services	0.170*	(0.102)
Eastern Germany	0.323***	(0.115)

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Table 2.4 – Continued

	Ordered logit	
	coeff.	se
Year of foundation[4]		
Founded in 1991	0.101	(0.404)
Founded in 1992	0.155	(0.439)
Founded in 1993	0.408	(0.387)
Founded in 1994	-0.069	(0.390)
Founded in 1995	0.575*	(0.345)
Founded in 1996	0.320	(0.315)
Founded in 1997	0.426	(0.312)
Founded in 1998	0.398	(0.313)
Founded in 1991	0.495	(0.312)
Founded in 2000	0.388	(0.314)
Founded in 2001	0.644*	(0.376)
Cut points		
α_1	-1.096***	(0.370)
α_2	-0.175	(0.369)
α_3	0.471	(0.370)
α_4	1.164***	(0.370)
Observations	1810	
Log-likelihood	-2590	
χ^2	438	

Notes: Categories of the dependent variable: 1 = still in science, 2 = time lag: 0-2 years, 3 = time-lag: 3-5 years, 4 = time-lag: 6-10 years, 5 = time-lag: above 10 years. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$, standard errors in parentheses. References: (1) competence spin-off, (2) single academic subject profile, (3) technological services, (4) founded in 1990.

Source: ZEW Spin-Off Survey 2001, author's calculations.

A negative coefficient in the ordered logit model implies that the marginal effect of the probability to be in the first category is positive. In this case, the marginal effect of the probability to be in category 5 is negative. The other way around, a positive coefficient impies that the marginal effect of the probability to be in the first category is negative while the marginal effect of the probability to be in category 5 is positive. The negative sign of the variable *team* thus implies that, ceteris paribus, the probability to be in the first group (still in science) is higher for team foundations than for single founders. Furthermore, the probability to be in the last group (time-lag: above 10 years) is less for team foundations than for single founders.

2.A2 Industry classification

Table 2.5: Industry classification: knowledge-intensive industries

NACE Rev.1	Description
Cutting edge technology (manufacturing)	
2330	Processing of nuclear fuel
2420	Manufacture of pesticides and other agro-chemical products
2441	Manufacture of basic pharmaceutical products
2461	Manufacture of explosives
2911	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
2960	Manufacture of weapons and ammunition
3002	Manufacture of computers and other information processing equipment
3162	Manufacture of other electrical equipment n.e.c.
3210	Manufacture of electronic valves and tubes and other electronic components
3220	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy
3320	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment
3330	Manufacture of industrial process control equipment
3530	Manufacture of aircraft and spacecraft
High-technology (manufacturing)	
2233	Reproduction of computer media
2411	Manufacture of industrial gases
2412	Manufacture of dyes and pigments
2413	Manufacture of other inorganic basic chemicals
2414	Manufacture of other organic basic chemicals
2417	Manufacture of synthetic rubber in primary forms
2430	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
2442	Manufacture of pharmaceutical preparations
2462	Manufacture of glues and gelatines
2463	Manufacture of essential oils
2464	Manufacture of photographic chemical material
2466	Manufacture of other chemical products n.e.c.
2912	Manufacture of pumps and compressors
2913	Manufacture of taps and valves
2914	Manufacture of bearings, gears, gearing and driving elements
2931	Manufacture of agricultural tractors
2932	Manufacture of other agricultural and forestry machinery
2940	Manufacture of machine tools
2952	Manufacture of machinery for mining, quarrying and construction
2953	Manufacture of machinery for food, beverage and tobacco processing
2954	Manufacture of machinery for textile, apparel and leather production
2955	Manufacture of machinery for paper and paperboard production
2956	Manufacture of other special purpose machinery n.e.c.
3001	Manufacture of office machinery
3110	Manufacture of electric motors, generators and transformers
3140	Manufacture of accumulators, primary cells and primary batteries
3150	Manufacture of lighting equipment and electrical lamps
3230	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods
3310	Manufacture of medical and surgical equipment and orthopaedic appliances
3340	Manufacture of optical instruments and photographic equipment
3410	Manufacture of motor vehicles
3430	Manufacture of parts and accessories for motor vehicles and their engines
3520	Manufacture of railway and tramway locomotives and rolling stock
Technology-intensive services	
642	Telecommunications
72	Computer and related activities (722: Software)
731	Research and experimental development on natural sciences and engineering
742	Architectural and engineering activities and related technical consultancy
743	Technical testing and analysis Non-Technical Consulting Services
2224	Pre-press activities
7133	Renting of office machinery and equipment, including computers
9211	Motion picture and video production
45114	Disaggregation of repositories
45120	Test drilling and boring

Continued on next page...

Table 2.5 – Continued

NACE Rev.1	Description
51146	Trade negotiation of office machines and software
51477	Wholesaling of precision and optical instruments and photographic equipment
51641	Wholesaling of office machines and software
52484	Retailing of precision and optical instruments and photographic equipment, computers and software
74201	Architectural and engineering activities and related technical consultancy
74704	Disinfection and pest control
74812	Photographic laboratories
74841	Fair and exhibition facilities
74844	Design studios
90009	Land reclamation and recultivation
91331	Education, science, research and culture organisations
92202	Production of radio and television programme
92324	Recording Studios
92325	Technical services for cultural and sustentative services
92522	Monument conservation
Knowledge-intensive services	
732	Research and experimental development on social sciences and humanities
7411	Legal activities
7412	Accounting, book-keeping and auditing activities; tax consultancy
7413	Market research and public opinion polling
7414	Business and management consultancy activities
744	Advertising
2214	Publishing of sound recordings
2215	Other publishing
6713	Activities auxiliary to financial intermediation n.e.c.
67203	Activities auxiliary to insurance and pension funding
74208	Business related technical consulting
74832	Translation activities
74842	Experts n.e.c.
74848	Supply of business related services n.e.c.
80422	Adult education
80424	Education a.n.g.
85144	Other self-employment in health care
92401	News agency activities
92521	Museums activities and art exhibitions

Remark: Differentiation according to the classification NACE Rev. 1 of the Statistical Office of the European Communities.
Source: Based on Egeln et al. (2003b), Grupp and Legler (2000)

2.A3 Transformations

In order to test the robustness of the data transformations which have been applied when estimating the Cox regression models, other data transformations, which still keep the ordering of the events, were applied and the same model specification was estimated. Cox regressions yield exactly the same result as with the original transformation.

The following transformations were made:

Transformation 1:

Cases:	new value	old value
Founders still in science:	time=0.12	time=0.1
Firm was established in the year of leaving:	time=0.25	time=0.2
Time-lag of one year:	time=1.3	time=1

Transformation 2:

Cases:	new value	old value
Founders still in science:	time=0.001	time=0.1
Firm was established in the year of leaving:	time=0.24	time=0.2
Time-lag of one year:	time=1.7	time=1
Time-lag of two years:	time=2.5	time=2

Transformation 3:

Cases:	new value	old value
Founders still in science:	time=0.001	time=0.1
Firm was established in the year of leaving:	time=0.24	time=0.2
Time-lag of one year:	time=1.7	time=1
Time-lag of two years:	time=2.5	time=2
Time-lag three years and more:	time=# years +0.034	time= # years

3 Employment growth in newly established firms

3.1 Introduction

Setting up one's own business is a far-reaching step in a person's vita. Several risks, financial and personal, must be born by the start-ups' founders. As manifold as founders' motives for starting a business, so are founders' choices for the point in time at which the company is be set up. The age of the founders highly varies, and entrepreneurs bring different levels of experience and qualification into the business. The consequences for firm performance are clear. Usually, higher human capital of a firm's founder is related to better firm performance. In empirical studies, founders' human capital is mostly proxied by their educational degree or professional experience, seldomly both are analyzed at the same time. Professional experience is typically assumed to enhance start-up performance, the more the merrier. By contrast, Müller (2006), who analyzed employment growth of academic spin-offs, found as a by-product of her study a significant negative sign of her control variable "job experience", measured by the difference between the year of foundation and the year in which the last founder has left academia. Furthermore, academic spin-offs are mostly not founded directly after university has been left but with a substantial "time-lag" (see chapter 2). The purpose of this chapter is to give a better understanding about what happens during this time and about the consequences of the length of the time-lags. I propose an explanation which states that the time which elapses between leaving the university and founding the start-up has strong implications on the total human capital endowment the founders bring into business. The academic knowledge is exposed to serious depreciation while the professional skills and the industry experience are being acquired. Using quantile regressions, I detect that a typical firm has the best growth prospects if the start-up is founded 3-5 years after the founder has left university. For academic spin-offs, i.e. those academic start-ups which are involved in the commercialization of new research results, the depreciation of academic knowledge has much stronger implications for future employment growth. The time which elapses after university has been left is of higher importance for academic spin-offs. A further key issue of this study is to investigate the importance of both firm-specific and founder-specific determinants of young firms' employment growth along the whole distribution of growth rates. For this purpose, quantile regressions are an adequate instrument. Also, the validity of the famous "Gibrat's Law", which has been tested almost exclusively in the conditional mean framework, is reexamined in the quantile regression framework. The next section reviews the literature on (young) firm's employment growth in detail. Section 3.3 develops the hypothesis about academic founders' human capital depreciation. Results of the empirical analysis are presented in section 3.4. Finally, the conclusions of this chapter are drawn in section 3.5.

3.2 Literature review

The determining factors of new firms' employment growth analyzed by empirical studies can be classified into three main groups: founder-specific factors, firm-specific factors, and external characteristics. Founders' human capital endowment is one of the most prominent founder-specific factors. Firm size, firm age, firm's innovation activities, its legal form, and its internationalization activities are usually classified as firm-specific factors. External characteristics are the surrounding business conditions which depend on the industry, the region, and the regulatory framework.

3.2.1 Size and age

One of the most famous theoretical concepts concerning the growth of a firm traces back to Gibrat (1931), who presents one of the first formal models of the dynamics of firm size (Sutton, 1998). His "Law of Proportional Effects", which is mostly interpreted as the proposition that firms grow proportionally and independent of their size, became generally known as Gibrat's Law. Gibrat's Law is included in numerous theories about firm growth, such as in the stochastic theory of Simon and Bonini (1958), who assume Gibrat's Law to apply for firms above the minimum efficient size level, and in a model of capital adjustments proposed by Lucas (1967), who supposes a firm's employment, output, and capital to follow the Law of Proportional Effects.

On the other hand, models of passive and active learning, as those by Jovanovic (1982) and Ericson and Pakes (1995), oppose the theories of Gibrat's Law - at least in the short run. In Jovanovic's model, firm growth is driven by firm's (cost) efficiency. Firms

do not know their efficiency ex ante and learn about it after they have entered the market. The hypotheses that firm growth decreases with age when initial firm size is held constant can be directly drawn from Jovanovic's model. Since the older firms have already learned about their efficiency and are not in need of further growth, young firms grow faster.
Models of optimum firm size also predict young and small firms to grow faster than large and mature firms because young firms usually start below their minimum efficient size and thus have a greater need to grow. Growth is essential if firms operate in industries with relevant economies of scale (Stam et al., 2007; Niefert, 2005).

A bulk of empirical studies concerning firms' employment growth has investigated the validity of Gibrat's Law. As most studies reveal that firms' growth decreases with size and age, Gibrat's Law is rejected for the U.S. (Sutton, 1998) and for most European countries (Audretsch et al., 1999). Mansfield's (1962) conjecture that the early empirical rejection of Gibrat's Law is a statistical artifact driven by a "sample censoring" problem, which is caused by a higher likelihood of exit of small firms with low growth rates, was addressed in literature of the late 1980s. Using techniques which account for sample selection and the presence of heterogeneity, Hall (1987), Evans (1987a,b), Dunne et al. (1989), and Dunne and Hughes (1994) find that firms' growth rates are decreasing in size, which is a robust rejection of the Law of Proportional Effects. This finding is at least true for small or young firms. For Germany, Wagner (1992) can reject Gibrat's Law for most groups of manufacturing firms in Lower Saxony. Likewise, Almus and Nerlinger (1999, 2000) show for young German manufacturing firms that the initial firm size is an important predictor for the future size and the employment growth. These results apply for firms operating in high-tech, medium-tech, and low-tech sectors in equal measure. By contrast, the evidence for service sectors is ambiguous. Mostly, Gibrat's Law is clearly rejected (Petrunia, 2008). However, in some cases, growth rates are independent of firm size for a subsample of the firms investigated (Audretsch et al., 2004).
Studies investing Gibrat's Law not in the conditional mean framework, but using quantile regressions, are extremely rare. To the best of my knowledge, only Lotti et al. (2003) have examined the influence of a firm's initial employment on future employment within the framework of conditional quantiles.[1] Using a sample of new manufacturing firms in Italy, they find Gibrat's Law to be invalid in the first years after entry.

[1]Two other studies by Reichstein et al. (2006) and Fotopoulos and Louri (2004) investigated Gibrat's Law for growth in sales and growth in total assets respectively.

The violation of Gibrat's Law becomes less severe for larger firms (Evans, 1987a). Hall (1987) finds Gibrat's Law accepted for the larger firms in her sample. Recent research (Lotti et al., 2009) regards Gibrat's Law to be rejected ex ante, i.e. in the early years of a firm's life-cycle, but detects a convergence toward Gibrat-like behavior ex post, i.e. a firm's employment growth follows Gibrat's Law after the firm has been fully developed. Therefore, Gibrat's Law is seen as a long-run regularity.

Most of the cited studies above do not only investigate the influence of firm size, but they concurrently study the influence of firm age on employment growth. They find that the growth decreases not only with firm size, but also with firm age.

Because of the mostly consistent results, the correlation of firm size and age with firm growth has become one of "stylized results of entry" (Geroski, 1995).

3.2.2 Innovation activities, legal form, and internationalization

The influence of innovation activities on employment growth is widely investigated in the literature. Most firm-level analyses for Europe are based on the Community Innovation Survey (CIS), a harmonized innovation survey on the European level. These studies concentrate on mature small and medium firms with more than 10 employees. Studies investigating the effect of innovation activities on employment growth of newly established firms are rather rare (see Niefert, 2005; Calvo, 2006; Almus, 2002).

The effect of a firm's innovation activity on its labor demand is a priori unclear. Direct supply-side effects of process innovations through labor-saving productivity gains allow a firm to produce the same output with less labor. The employment growth after implementing new processes might thus be lower. If the firm passes on cost advantages to customers through price reductions, positive (indirect) demand-side effects arise as demand increases. The total effect of process innovations on employment growth can even be positive if the demand-side effects compensate for the negative effect of labor-saving productivity gains.

Similarly, two opposing effects of product innovation and market novelties on labor demand can be distinguished. First, the introduction of new products stimulates new demand for a firm's products and thus increases firm's labor demand. Second, new products, especially products new to the market, can open up a temporary monopoly.

Under profit maximizing assumptions, a firm will exploit its monopoly power, i.e. raise the product's price above marginal costs through output reduction, and reduce its labor demand (Smolny, 1998; Blechinger et al., 1998). Katsoulacos (1986) theoretically derives a positive total effect of product innovations and a negative total effect of process innovations.

When measuring innovation activities, most empirical studies distinguish between input and output measures. Innovation input is often defined as conducting R&D. The implementation of new products or processes is used as direct output measures. Patents can be seen as intermediate innovation output. However, they are often claimed to be a flawed measure of innovation output (Acs et al., 2002).

R&D is often found to be positively correlated with employment growth (Blechinger et al., 1998; Regev, 1998). Furthermore, most empirical studies detect a positive effect of product innovations on labor demand (Van Reenen, 1997; Blechinger et al., 1998; Smolny, 1998, 2002; Greenan and Guellec, 2000; Jaumandreu, 2003; Peters, 2004; Lachenmaier and Rottmann, 2007; Harrison et al., 2008). Evidence for process innovations is not as clear-cut as for product innovations. Some studies find a positive effect for process innovations (Smolny, 1998, 2002; Lachenmaier and Rottmann, 2007) while others find either no effect (Van Reenen, 1997; Jaumandreu, 2003) or a negative effect (Peters, 2004; Harrison et al., 2008).

The evidence for young firms is similar. Niefert (2005) finds that patenting has a positive effect on the employment growth, and Calvo (2006) detects a strong positive influence of both process and product innovations on employment growth in young Spanish firms.

Concerning the legal form, firms with limited liability are expected to have higher growth potentials. Owners of these firms are not liable with their own fortune. Therefore, incentives for taking risky projects, which yield higher returns on investments, are higher for firms with limited liabilities conditional on surviving (Stiglitz and Weiss, 1981). This relationship is supported in studies by Harhoff et al. (1998) and Davidsson et al. (2002) for mature firms as well as in studies by Engel (2002) and Almus and Nerlinger (1999) for newly founded firms.

Another line of the literature on firm growth addresses the export-growth relationship. Theoretically, exporting improves firm performance because serving a larger market allows a firm to exploit economies of scale and to cope with domestic demand variations. But a firm which serves foreign markets has to bear additional cost. Therefore, only healthy firms will engage in exporting (Wagner, 2002). Two facts turned out to be of importance: First, growth rates are higher for exporting firms ex-ante, i.e. successful firms are more likely to become exporters. Second, benefits from exporting occur in terms of increased employment growth and a higher likelihood of survival but not in terms of productivity growth (Bernard and Jensen, 1999). Using matching techniques, Wagner (2002) shows that there is a causal effect from exporting on a firm's performance in terms of employment growth. For young high-tech firms, Bürgel et al. (2004) support these results for sales growth, but not for employment growth.

3.2.3 Founders' human capital

The human capital endowment of a firm's founders is seen as an important factor influencing the growth path of that firm. Founders' human capital affects firm success by means of founders' productivity, particularly by developing a business plan which directs investment towards those areas of business activity that will generate the highest returns. Moreover, greater human capital increases founders' productivity in terms of organizing and managerial efficiency and acts as a positive signal for the firm's prospective stakeholders (investors, customers and suppliers). These parties usually have imperfect information about the firm's potentials and will benchmark the firm by means of observable characteristics, such as founders' human capital. Therefore, firm success should be higher for the founders with a rich human capital endowment (Brüderl et al., 1992; Bosma et al., 2004).

Van Praag and Cramer (2001) have developed a formalized model of human capital's impact on a firm's labor demand. In equilibrium, labor demand of a firm is positively influenced by the individual's entrepreneurial talent. The estimation of a therefrom derived structural empirical model confirms the predictions of their theoretical model.

Following Becker (1993), human capital is traditionally distinguished into general human capital and specific human capital. In entrepreneurship research, general human capital is usually measured in terms of schooling and overall work experience, as it is done in traditional labor economics. Specific human capital is mostly approximated by industry-specific knowledge and prior self-employment experience. Usually, survival probabilities are higher, the higher the human capital endowment of the founders.

Concerning work experience, a concave relationship applies (Brüderl et al., 1992). This concavity might be driven by age-effects. Founders with a very long working-experience have mostly reached a high age in which flexibility as well as physical and mental fitness are limited.

Almus (2002) finds that new enterprises of persons with a very high human capital endowment are more likely to become fast growing firms. For new technology-based firms, Almus and Nerlinger (1999) show that human capital, which is measured by a technical degree of the founders, is positively correlated with the firm's employment growth. Similarly, Moog (2004) shows that founders with a university degree realize higher employment growth, both for employees in general and for the highly qualified employees.

The influence of different components of founders' human capital on the growth of new technology-based firms is investigated in detail by Colombo and Grilli (2005a), Bosma et al. (2004) and Koeller and Lechler (2006). They find that the nature of founders' education as well as prior work experience - most notably experience in the same industry - are the key determinants of new firm growth. The most important conclusion drawn from their analysis is that founders' human capital is a proxy not only for the founders' personal wealth but also for their capabilities.

The influence of the composition of founders' human capital on employment growth in academic spin-offs has been investigated by Müller (2006). She finds that the human capital composition, i.e. specialization versus being a generalist, is irrelevant for academic spin-offs' employment growth. However, founding in a team is related to higher employment growth. This corresponds with earlier literature (Eisenhardt and Schoonhoven, 1990; Reynolds, 1993). In this line of literature, forming a team is seen as a way for compensating individual deficits of one team member by the strengths of other team members.

3.3 The depreciation of academic knowledge

The possibility of the depreciation of human capital has almost exclusively been investigated for employees since it has become common to decompose net investments in human capital as a predictor of a person's earnings into gross investments and depreciation. Depreciation rates in times of career interruptions are estimated by assuming that gross investments are zero during career interruptions.

Depreciation rates of either voluntary, mostly family-related, or involuntary career interruptions, such as unemployment or sick leave, have been estimated in terms of forgone earnings. Most commonly, researcher use an adapted and extended version of Mincer's (1974) earning function (e.g. Mincer and Polachek, 1974, 1978; Mincer and Ofek, 1978; Beblo and Wolf, 2000; Görlich and de Grip, 2007).

Already Mincer and Polachek (1974) have noticed that the depreciation of human capital's earning power may occur not only during periods of nonparticipation at the labor market, but during participation periods as well. Only a few studies (Groot, 1998; Arrazola and de Hevia, 2004) address the question of human capital depreciation during employment spells. Human capital depreciation during employment spells has been specified in earning functions of earlier work, but it has not yet been estimated explicitly. Non-linear methods enable Groot (1998) as well as Arrazola and de Hevia (2004) to estimate the rate of human capital depreciation without the use of career interruption spells.

Another study of Neumann and Weiss (1995) deals with human capital depreciation by investigating the shape of worker's experience-earning profiles. They find different peaks in the experience-earnings profile for people working in high-tech and low-tech industries. Furthermore, experience-earning profiles are steeper for highly educated people. This procedure implicitly assumes that human capital depreciation due to workers' aging and the obsolescence of knowledge is present also during the participation at the labor market.

Human capital depreciation has thus proved to be present for employees. Since the human capital endowment of a firm's founders has been shown to be a major determinant of a new firm's success, the concept of human capital depreciation needs to be implemented and investigated by entrepreneurship research, too. This study is an attempt in doing so.

The investigation in this study follows the theory of heterogeneous human capital. Some parts of the human capital might even depreciate if there are no career interruptions. Particularly with regard to academic knowledge, depreciation might become severe once university is left since scientific techniques fall into oblivion if they are not used

continuously. Furthermore, academic knowledge might become obsolete and its value might decrease if one does not keep pace with scientific progress. I distinguish two main types of human capital which are relevant for employment growth in academic start-ups. Human capital of academic start-ups' founders is determined by the stock of their *academic knowledge* and the stock of their *professional experience*.
Academic knowledge is accumulated during a founder's time in academia. At the point in time when the academic institution is left, the stock of a person's academic knowledge is highest. Instantaneously, the depreciation of a person's academic knowledge begins because the skills fall into oblivion if they are not used, and they might become obsolete as time passes by. Hence, the academic knowledge A of an academic firm founder is a decreasing function in t, the time which elapses after leaving university and founding the start-up. Therefore, $A(t) > 0$ and $\frac{\partial A(t)}{\partial t} < 0 \;\; \forall t$.

While academic knowledge depreciates, professional experience P is gained. Professional experience of new firm founders is essential as both knowledge about the industry and the organization of a firm is acquired. Possibly, the prospective founder could even gain management experience during that time. In this context, professional experience P is expected to be accumulated with positive but decreasing returns over time. Therefore, $P(t) > 0$, $\frac{\partial P(t)}{\partial t} > 0$, and $\frac{\partial^2 P(t)}{\partial t^2} < 0 \;\; \forall t$.

Concerning how the total human capital HC of a founder is influenced by the stock of academic knowledge and professional experience, let us consider two extreme cases: Either academic knowledge and professional experience complement each other or they are perfect substitutes.

If they are perfect complements, $HC(t) = \min\left[\alpha A(t), \beta P(t)\right]$. The parameter $\alpha > 0$ denotes the weight assigned to academic knowledge, and $\beta > 0$ denotes the weight assigned to professional experience. That means,

$$HC(t) = \begin{cases} \alpha A(t) & \text{if} \quad \alpha A(t) \leq \beta P(t), \\ \beta P(t) & \text{if} \quad \alpha A(t) > \beta P(t). \end{cases}$$

As long as one assumes the professional experience to increase over time ($\frac{\partial P(t)}{\partial t} > 0$) and the academic knowledge to depreciate continuously after leaving university ($\frac{\partial A(t)}{\partial t} < 0$), total human capital peaks at $\alpha A(t) = \beta P(t)$.

The other way around, if academic knowledge and professional experience are perfect substitutes, i.e. $HC = \alpha A(t) + \beta P(t)$, the first order condition for a maximum is given by

$$\frac{\partial HC}{\partial t} = \alpha\frac{\partial A(t)}{\partial t} + \beta\frac{\partial P(t)}{\partial t} = 0 \quad \Leftrightarrow \alpha\frac{\partial A(t)}{\partial t} = -\beta\frac{\partial P(t)}{\partial t}.$$

That is, total human capital of prospective entrepreneurs peaks when the weighted marginal products are equal, provided that the second order condition $\frac{\partial^2 HC}{\partial t^2} < 0$ is fulfilled.

$$\frac{\partial^2 HC}{\partial t^2} = \alpha\frac{\partial^2 A(t)}{\partial t^2} + \beta\frac{\partial^2 P(t)}{\partial t^2}$$

Since $\frac{\partial^2 P(t)}{\partial t^2} < 0$ by assumption, and $\frac{\partial^2 HC}{\partial t^2} < 0$ if $-\frac{\frac{\partial^2 A(t)}{\partial t^2}}{\frac{\partial^2 P(t)}{\partial t^2}} < \frac{\beta}{\alpha}$, the condition $\frac{\partial^2 A(t)}{\partial t^2} < 0$ would ensure that a maximum exists.

Having $\frac{\partial^2 A(t)}{\partial t^2} < 0$ seems to be rather plausible at least for small t since one can possibly expect the depreciation of founder's academic knowledge to be disproportionately high at least at the beginning while the depreciation might become less severe after some years have passed by (for illustration see middle graph in Figure 3.1). This is reasonable since basic skills which have been acquired at university remain present even after decades.

Figure 3.1 illustrates how the total human capital is composed of academic knowledge and professional experience. The upper graph depicts how professional experience is accumulated after university has been left. Similarly, the middle graph illustrates how the stock of academic knowledge might evolve over time once university is left.

Consequently, as the elapsing time affects the two components of entrepreneur's human capital in opposite directions, founding is neither best directly after leaving the university nor after a very long time. The graph at the bottom of Figure 3.1 illustrates the combined effect of the time after leaving academia, but before founding, on the total human capital endowment of the prospective entrepreneur.

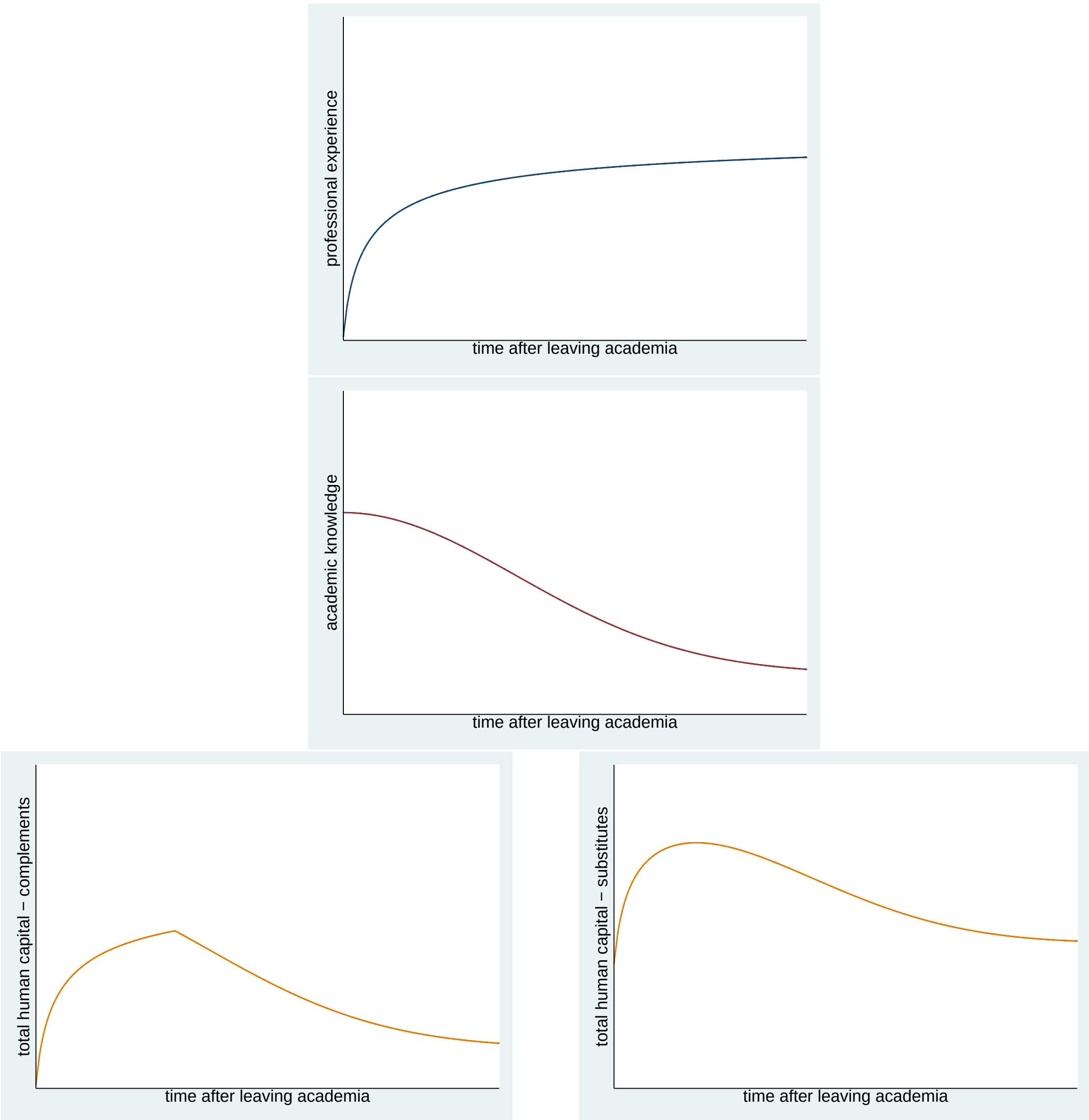

Figure 3.1: Graphical illustration of founder's human capital development after leaving university

Note: Graphical illustration of the development of entrepreneur's human capital after leaving university if professional experience and academic knowledge are perfect complements (left) or perfect substitutes (right).
Source: Author's illustration.

The picture on the left illustrates the development of the entrepreneurial total human capital if academic knowledge and professional experience are perfect complements. The picture on the right depicts this development if academic knowledge and professional experience are perfect substitutes and if the second order condition is fulfilled. Total human capital is increasing at the beginning. At some point in time, human capital peaks and decreases thereafter. Because total human capital of the founders is directly linked to employment growth, founders who have started their firms close to the peak of their total human capital endowment should reveal the best growth prospects.

The hypothesis to be tested in the next part of this chapter states the following:

Hypothesis 1a: *The influence of the time which elapses after a founder has left the academic institution on firms' employment growth is inverse u-shaped.*

For academic spin-offs, i.e. those start-ups which have greatly contributed to the commercialization of research results, obsolescence of academic knowledge is of higher importance. If the business idea rests upon new research results or newly developed scientific methods (so-called "academic spin-offs"), rapid technology changes and catching-up processes might require that the venture is started earlier. Speaking in terms of the graph at the bottom of Figure 3.1: For spin-offs, the human capital peak is located to the left of ordinary academic start-up's human capital peak. Therefore, the hypothesis is supplemented as follows:

Hypothesis 1b: *The influence of the time which elapses after a founder has left the academic institution on firms' employment growth is inverse u-shaped* ***and differs between academic start-ups and academic spin-offs****.*

3.4 Empirical Analysis

3.4.1 Growth model and estimation method

Employment growth of academic start-ups is modeled by assuming an exponential growth path, which has been suggested by Evans (1987a,b) and adopted by a number of other studies investigating the growth of young firms (e.g. Almus and Nerlinger, 1999; Almus, 2002). The number of employees (including the owners) S_{i2008} in firm i at the beginning of 2008 is determined as follows:

$$S_{i2008} \quad = \quad [exp(\boldsymbol{x}_i^{'}\boldsymbol{\beta}) \cdot G(A_{i2008}, S_{iT})]^{A_{i2008}}(S_{iT})e_i.$$

S_{iT} denotes the number of employees in the founding year in firm i, A_{i2008} the age of the start-up in 2008 and e_i is the error term. $G(\cdot)$ is a function of age A_{i2008} and initial size S_{iT}. Firm size in 2008 is further determined by variables contained in vector $\boldsymbol{x}_i$. The vector $\boldsymbol{x}_i$ contains founder- and firm-specific variables, particularly the time which elapsed after the last founder has left academia.[2]

Taking logarithms and rearranging yields for the annual growth rate

$$y_i = \frac{ln(S_{i2008}) - ln(S_{iT})}{A_{i2008}} \quad = \quad \boldsymbol{x}_i^{'}\boldsymbol{\beta} + ln(G(A_{i2008}, S_{iT})) + u_i. \tag{3.1}$$

Equation 3.1 is estimated using quantile regressions. This estimation technique, which models the different conditional quantiles of a specific distribution, was introduced by Koenker and Bassett (1978). Traditional estimation techniques focus on the estimation of the conditional mean of the response variable. But focusing solely on the "average" firm is not always appropriate, as Mosteller and Turkey (1977, p. 266) note:

> "What the regression curve does is give a grand summary for the averages of the distribution corresponding to the set of x's. [...] Just as the mean gives an incomplete picture of a single distribution, so the regression curve gives a correspondingly incomplete picture for a set of distributions."

Investigating young firm's employment growth, we are especially interested in the determinants of exceptional high growth as well as in the causes of being at the lower tail of the growth distribution. Therefore, quantile regressions provide a possibility to get a more complete picture in analyzing the driving factors of employment growth along the entire conditional distribution.

Additionally, quantile regression techniques provide some advantages compared to mean-oriented regression techniques. First, for highly-skewed or heavy-tailed distributions, the mean does not only give an incomplete picture of the distribution,

[2]See section 3.4.2 for a detailed description of the variables included.

but is likewise challenging to interpret. As highly growing firms are a real-world phenomenon and not necessarily data errors, there is no room for removing those observations as it is often done in the conditional-mean framework. Second, quantile regressions are especially suitable for heteroscedastic data. A third advantage of quantile regressions is their monotone equivariance which allows to measure the impact of a covariate both in relative and absolute terms using one model.

Analyses which model the conditional median and other quantiles often turn out to be more appropriate as they show up an inherent robustness to outliers.

The parameters in the quantile regression framework are estimated by minimizing the weighted sum of absolute residuals. The growth model is then written as

$$\begin{aligned} y_i &= \boldsymbol{x}_i^{'}\boldsymbol{\beta}_\theta + ln(G_\theta(A_{i2008}, S_{iT})) + u_{i\theta}, \\ &\text{with} \quad Q_\theta(y_i|\boldsymbol{x}_i, A_{i2008}, S_{iT}) = \boldsymbol{x}_i^{'}\boldsymbol{\beta}_\theta + ln(G_\theta(A_{i2008}, S_{iT})). \end{aligned} \tag{3.2}$$

Q_θ denotes the θth conditional quantile of firms' annual logarithmic change in employment (y_i). The θ^{th} regression quantile, $0 < \theta < 1$, is the solution of the following minimization problem, which can be solved by linear programming methods:

$$\min_{\boldsymbol{\beta}_\theta} \sum_{i:y_i \geq Q_\theta} \theta|y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta}_\theta - ln(G_\theta(A_{i2008}, S_{iT}))| + \sum_{i:y_i < Q_\theta} (1-\theta)|y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta}_\theta - ln(G_\theta(A_{i2008}, S_{iT}))|.$$

Interpreting the coefficients estimated by quantile regressions is as easy as interpreting OLS coefficients. The coefficient β_θ represents the change in y at the θ^{th} conditional quantile due to a marginal change (zero-one change for dummy variables) in the corresponding regressor. For logarithmic transformations of dependent and independent variables, the same interpretation rules in terms of semi-elasticities and elasticities apply as in the OLS framework.

Additional information on quantile regression techniques can be found in Hao and Naimann (2007), Koenker and Bassett (2001) or Buchinsky (1998).

3.4.2 Database and descriptive Statistics

The empirical analysis is based on a data-set of more than 10,000 German start-ups in research- and knowledge-intensive industries founded between 2001 and 2006. For constructing this data-set, a computer-assisted telephone survey was conducted in the first quarter of 2008. The stratified random sample[3] was drawn from the Mannheim Enterprise Panel, which is build upon information of Germany's largest credit rating agency Creditreform and covers data on all start-up companies in Germany.
The conceptual design of this survey is based on an earlier survey of the Centre for European Economic Research (ZEW), the ZEW Spin-Off Survey 2001, which was conducted in order to estimate the yearly number of academic spin-offs in Germany in the period between 1996-2000 and the core characteristics of these spin-offs.[4]

The new survey covers a wide range of founder-related and firm-related information. For the purpose of learning about founders' academic background, information about founders' highest formal educational degree has been retrieved during the interview.
For academic founders, the year was recorded when they had left academia. With this information, the spell from leaving academia up to the point in time when the establishment of the firm has taken place can be calculated.[5]
Furthermore, firm-level information concerning the year of establishment, financial and other retrieved support, employment, turnover, innovation activities, and academic networking was collected.

As the purpose of the analysis in this chapter is to investigate the human capital depreciation of academic founders, only academic start-ups (start-ups of students, graduates, or academic researchers) are included in the empirical analysis. Out of 10,126 start-ups surveyed, 4,303 firms could be identified as academic start-ups with non-missing values for the variables under investigation. Those start-ups were used for the quantile regressions which will be presented in section 3.4.3. Using only academic start-ups for the analysis implies that the founders have a similar educational level. This fact allows me to distinguish the depreciating effects of the time which elapses after leaving academia on human capital and its influence on employment growth.

[3]Stratification criteria are the year of establishment, industry and type of region
[4]For further information about that data-set see Egeln et al. (2003a)and chapter 2.
[5]In case of establishments in teams the year when the *last* founder left academia was recorded.

Following the hypothesis that the effect of academic knowledge depreciation differs between ordinary academic start-ups and academic spin-offs, it is necessary to define which start-ups can be classified as academic spin-offs. Academic spin-offs are only those academic start-ups which substantially contribute to technology transfer from academia. This has been classified according to the founders' self-assessment. During the interview founders of academic start-ups were asked about the relevance of own, newly generated research results and the relevance of new scientific methods for the creation of the firm. If either own research or the acquisition of new scientific methods has been *indispensable* for venture creation, the contribution to technology transfer can be assessed as high enough to refer to these ventures as to academic spin-offs.[6] This approach of defining academic spin-offs was first adopted by Egeln et al. (2003a) following Mansfield's (1995) method in identifying technology transfer from academic research. Using this approach, the sample of 4,303 academic start-ups contains 301 academic spin-offs.

Table 3.1: Detailed description of the annual logarithmic change in employment

	employment growth	
Mean	0.141	
Standard deviation	0.210	
Skewness	1.385	*** (a)
Kurtosis	8.025	*** (a)
Q5	-0.096	
Q10	0.000	
Q25	0.000	
Median	0.099	
Q75	0.231	
Q90	0.393	
Q95	0.536	
Shapiro-Francia test	0.912	***
Kolmogorov-Smirnov test	0.177	***

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;
(a) Rejection of normality based on skewness and kurtosis test for normality.
Source: ZEW Spin-Off Survey 2008, author's calculations.

According to the growth model presented in section 3.4.1, employment growth is calculated as annual logarithmic change in employment between 2008 and the founding year. Average growth is 14 percent, median growth is 10 percent. The distribution

[6]Note that the approach in chapter 2 is wider.

of employment growth is positively skewed. Various measures, e.g. the Kolmogorov-Smirnov test, indicate that employment growth deviates from the normal distribution (see Table 3.1).

Besides the description of the variables below, a summary table including a short description and the descriptive statistics of all independent variables included in the analysis is provided in the appendix.

The central variable, the time that elapses between leaving academia and starting a venture, is measured in categories. This is done because the time-lag after leaving academia is left-censored if the founder has been still in academia when the firm was founded. An example will help to understand the censoring problem. Due to the survey design, two possible cases might occur: If the founder has left university in 2006 and has already established his business in 2004 the founder's corresponding time-lag can be calculated and is -2 years. For those founders who have established their business, for example, in 2006 and have still been in academia when the survey was conducted (in the beginning of 2008) it is only known that the time-lag is less or equal than 2 years.

Omitting these observations would cause a severe bias. Building categories for different length of time-lags solves this problem because all observations can be used. No valuable information is lost since the depreciation of academic knowledge will occur not until leaving university. Therefore, I focus on positive time-lags. Six categories of the time-lag between leaving academia and firm formation are built and included in the analysis using dummy variables. The category of a time-lag from zero up to two years serves as reference category. In order to capture different effects of human capital depreciation between academic spin-offs and ordinary academic start-ups, interactions of all categories with a dummy which measures if the start-up can be classified as a spin-off are included in the regressions. Most academic start-ups have a time-lag of 11-20 years (see Table 3.2). This is not surprising since the average age of founders in Germany is around 40 years. A non-negligible fraction of academic start-ups is founded either while at least one of the founders is still in academia (17 percent) or shortly after the founder has left academia (10 percent).

After leaving academia, founders of academic start-ups accumulate professional experience as well as industry experience, but they are exposed to a depreciation of their academic knowledge. If founders have been unemployment during that time a smaller

Table 3.2: Time-lag since academia was left

	Mean	Std. dev.
Still in academia	0.170	(0.375)
Time-lag: 0-2 years	0.101	(0.302)
Time-lag: 3-5 years	0.115	(0.319)
Time-lag: 6-10 years	0.179	(0.384)
Time-lag: 11-20 years	0.260	(0.439)
Time-lag: +20 years	0.174	(0.379)

Source: ZEW Spin-Off Survey 2008, author's calculations.

amount of professional experience could has been acquired than the time-lag supposes. Moreover, a depreciation of their human capital gained by means of professional experience can have taken place. For this reason, a further dummy variable is included which indicates if one of the founders has faced a longer unemployment spell.

In order to control for the well documented relationship between size, age, and employment growth and to test the validity of Gibrat's Law for young firms in the research- and knowledge-intensive industries, initial firm size and firm age are included in the analysis. Initial employment enters the equations in logarithms and its square term. Age is captured by a set of dummy variables. This approach offers the most flexible functional form concerning how age influences employment growth. Furthermore, the dummies can capture possible "year-effects" of economic cycles during that time.

A large set of further independent variables is included into the regressions which have been detected by theoretical and empirical studies to have significant influence on firm's employment growth.

Those are dummy variables which measure if the firm is active in exporting, if the establishment has taken place in a team of founders and if the legal form of the company involves a limited liability of firm's owners.

Three dummy variables capture innovative activities. Two of them show if the start-up is conducting continuous or occasional R&D, the third dummy variable indicates if the start-up has introduced novelties to the market.

So far, determinants of young firms' employment growth have been investigated almost solely in the conditional mean framework. Therefore, this study not only contributes to the investigation of the effect of entrepreneur's human capital depreciation on firms' employment growth but also to the reassessment of common effects within the framework of median regressions. Furthermore, in a quantile regression framework the influence of these variables on noncentral positions, i.e. on different quantiles, of the growth distribution can be shown. Beyond that, if those variables proof to be significant in this model of human capital depreciation, robustness of the whole model will be indicated.

Financial constraints are of high relevance especially for young firms (Oliveira and Fortunato, 2006; Cabral and Mata, 2003; Westhead and Storey, 1997). If budget constraints are softened by state subsidies, firms are found to have higher rates of employment growth (Becchetti and Trovato, 2002). The impact of external public support on young firms' employment growth is also addressed in my analysis. Public subsidies in terms of grants or soft loans are expected to relax financial constraints the firm faces. Public funding is differentiated into public funding from the Federal Employment Agency (Bundesagentur für Arbeit - BA) and public funding from other public agencies, such as special credit institutions (*Kreditanstalt für Wiederaufbau (KfW)* and *Landesförderbanken*), federal and state ministries, municipalities, the EU, and the Chamber of Industry and Commerce.

Public funding from the Federal Employment Agency is granted to unemployed persons who start their own business. The volume of financial support from the Federal Employment Agency is rather low since it primarily aims to ease the transition into self-employment and to ensure the founder's cost of living in the first months. This dummy variable might thus not only capture a potential relaxation of financial constraints but poor growth prospects of start-ups the founders of which are first and foremost motivated by getting out of dire straits. Around 10 percent of all academic start-ups in the sample received funding from the BA.

On the other hand, financial funding from other public agencies, which has been granted to about 16 percent of the academic start-ups, is not driven by labor market programs but industrial policy. Usually, these programs intend to foster competitiveness and economic growth by supporting start-ups. Funding amounts of these programs are considerably larger and thus more likely to be able to relax financial constraints.

Another way of public, but non-financial support is housing of new ventures in science parks or business incubators. In fact, 6 percent of all academic start-ups in the sample have been hosted by a science park or business incubator. This infrastructural support might also relax financial constraints, back new firm's business success and therefore enhance firm's labor demand.

Networking effects, which have been shown to exert influence on employment growth in the analysis of Stam et al. (2007), are accounted for by including dummy variables which indicate different types of regular contacts to academia. Additionally, the depreciation of academic knowledge might proceed not as fast if the founders stay in contact with academia.

External characteristics, which are not explicitly investigated in this study, are controlled for by industry dummies. As the analysis is restricted to academic start-ups in research- and knowledge-intensive industries, external characteristics might not differ too much between the firms. In contrast to other studies, this analysis is not restricted to manufacturing firms only, as it is the case in Almus and Nerlinger (1999). According to their NACE 4-digit codes, start-ups in the research- and knowledge-intensive industries are subdivided into high-technology industries, technology-intensive services and knowledge-intensive services.[7] High-technology industries are manufacturing sectors which exhibit an average R&D-intensity above 3.5 percent, e.g. manufacturing of pharmaceutical and chemical products. 24 percent of the firms in the sample belong to the high-technology industries. 35 percent of the academic start-ups investigated belong to the technology-intensive services (telecommunications, software etc.). This group serves as reference category. Most firms (41 percent) belong to the knowledge-intensive services, e.g. consultancy.

Furthermore, using a dummy variable, I control for the possibility that a start-up is not growth-oriented. It is necessary to control for that motive since it is frequently monitored that founders prefer to stay small. For example, Storey (1994) detected that about 50 percent of UK founders start their firms with no intention to grow. In our sample, this is true for 34 percent of all start-ups investigated.

[7] A classification list based on NACE codes is provided on in the Appendix to chapter 2.

3.4.3 Estimation results

Equation 3.2 is estimated for 19 quantiles (0.05, 0.10, 0.15 etc.) simultaneously. Inference is based on bootstrapped standard errors using 500 replications. Results for the median regression are displayed in Table 3.3 and compared to OLS regression of the same model. The hypothesis of entrepreneur's human capital depreciation is confirmed both for the OLS regression and for the median regression . The impact of the time-lag after university has been left is inverse u-shaped with a peak of human capital endowment roughly around 3-5 years. Employment growth is around 4 percent higher if an academic start-up is founded with a professional experience of 3-5 years instead of an experience of 0-2 years (reference group). When the time-lag is 6-10 years, employment growth is 3 percent lower at the median. Interpreting these results, one has to consider that the time-lag might not only comprise the depreciation and accumulation of human capital but might also capture the age and financing options of the founders, which unfortunately cannot be included in the analysis since such information has not been part of the survey.

Furthermore, the coefficients of the interaction effects show that the relationship between human capital and employment growth is different when academic spin-offs are examined. With a founding time-lag of 3-5 years employment growth in academic spin-offs is 1.7 percent ($= 0.040 + (-0.057)$) lower than in academic start-ups with a founding time-lag of 0-2 years. After 6-10 years employment growth is even 6.6 percent lower. However, starting the venture while at least one of the founders is still in academia is not advantageous for academic spin-offs. Common effort of all founders of academic spin-offs seems to be needed in the early stages of firm's development. This result is in line with an observation of Doutriaux (1987). He finds that manufacturing firms grow less if its academic founder is still employed by the university.

Table 3.3: OLS and median regression on employment growth

	OLS		Q50	
	coeff.	se	coeff.	se
Time-lag since academia was left[(1)]				
Still in science	0.005	(0.011)	0.007	(0.011)
Time-lag: 3-5 years	0.033***	(0.012)	0.040***	(0.014)
Time-lag: 6-10 years	0.025**	(0.011)	0.030**	(0.012)
Time-lag: 11-20 years	0.015	(0.010)	0.006	(0.011)
Time-lag: +20 years	-0.025**	(0.011)	-0.024**	(0.011)
(Spin-off)*(still in science)	-0.041**	(0.020)	-0.034*	(0.019)
(Spin-off)*(0-2 years)	0.001	(0.023)	-0.020	(0.030)
(Spin-off)*(3-5 years)	-0.053*	(0.029)	-0.057*	(0.031)
(Spin-off)*(6-10 years)	-0.074***	(0.028)	-0.096***	(0.028)
(Spin-off)*(11-20 years)	-0.031	(0.028)	0.029	(0.032)
(Spin-off)*(+20 years)	0.015	(0.037)	-0.019	(0.043)
Log(size)	-0.070***	(0.010)	-0.014	(0.010)
Log(size)^2	0.000	(0.003)	-0.011***	(0.003)
Year of foundation[(2)]				
Founded in 2002	0.015**	(0.007)	0.013*	(0.007)
Founded in 2003	0.036***	(0.007)	0.026***	(0.008)
Founded in 2004	0.057***	(0.008)	0.040***	(0.009)
Founded in 2005	0.106***	(0.009)	0.070***	(0.012)
Founded in 2006	0.126***	(0.012)	0.049***	(0.014)
Innovation activities				
Continuous R&D	0.024**	(0.009)	0.016*	(0.009)
Occasional R&D	0.001	(0.010)	-0.002	(0.009)
Market novelties	0.033***	(0.008)	0.036***	(0.008)
Science park	0.029**	(0.013)	0.029**	(0.013)
Public funding (BA)	-0.031***	(0.010)	-0.038***	(0.010)
Public funding (non-BA)	0.031***	(0.008)	0.033***	(0.009)
Limited liability	0.058***	(0.008)	0.053***	(0.008)
Exports	0.060***	(0.006)	0.057***	(0.007)
Team	0.010	(0.008)	0.004	(0.008)
No-expansion strategy	-0.061***	(0.006)	-0.056***	(0.007)
Unemployed	-0.072***	(0.019)	-0.027	(0.019)

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Table 3.3 – Continued

	OLS		Q50	
	coeff.	se	coeff.	se
Contacts to academia				
Joint research contacts	-0.014	(0.015)	-0.001	(0.015)
Contract research contacts	0.000	(0.022)	-0.000	(0.018)
Customer contacts	0.015	(0.013)	0.018*	(0.011)
Continuing education contacts	0.046***	(0.016)	0.045***	(0.014)
Industry$^{(3)}$				
High-technology manufact.	0.009	(0.008)	0.018**	(0.009)
Knowledge-intensive services	0.009	(0.007)	0.008	(0.007)
Constant	0.068***	(0.011)	0.031**	(0.012)
Observations	4303		4303	
R^2 / Pseudo R^2	0.190		0.113	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust (OLS) or bootstrapped (Q50) standard errors in parentheses. References: (1) start-up with time-lag: 0-2 years, (2) founded in 2001 (3) technology-intensive services.

Source: ZEW Spin-Off Survey 2008, author's calculations.

Table 3.5 shows the regression results for the most but, due to shortage of space, only selected quantiles. Human capital depreciation is of relevance, especially for fast-growing academic spin-offs. Coefficients for the time-lag dummies are for most instances insignificant for non-growing firms (5 percent - 25 percent quantile) while the coefficients increase over the quantiles.

However, differences for growing firms are mostly not statistically significant, except for the difference between the 40 percent quantile and the 75 percent quantile and the difference between the 40 percent quantile and the 80 percent quantile for a time-lag of 3-5 years. Additionally, significant differences for the coefficient *(Spin-off)*(6-10 years)* can be observed between the 40 percent and 70 percent quantile and between the 40 percent and 50 percent quantile. Human capital depreciation has no effect on a firm's employment growth in the lower quantiles, in which firms are not growing. Almost all coefficients measuring the human capital depreciation are insignificant at the 5, 10, and 25 percent quantiles.

Interesting insights can also be obtained from the estimated effects of the control variables. Over the whole distribution, a significant impact of initial firm size and firm age on a firm's employment growth can be observed. Following learning theories of firm growth (Jovanovic, 1982), capital adjustment theories of firm growth (Lucas, 1967, 1978), stochastic theories of firm growth (Simon and Bonini, 1958), or evolutionary theories of firm growth (Neslon and Winter, 1982), Gibrat's Law can be rejected if

$$g_s = \frac{\partial lny}{\partial lnS_T} = \beta_{ln(S_T)} + 2 \cdot \beta_{ln(S_T)^2} ln(S_T) \neq 0,$$

which is the partial derivative of the logarithmic growth rate with respect to firm size (see Evans, 1987b). At sample median and for the regression results of the median regression $g_S = -0.277$, which is significantly different from zero.

Table 3.4: Testing Gibrat's Law along the conditional growth distribution

Quantile	(1) $g_S = \frac{\partial y}{\partial ln(S_t)}$	(2) $E_S = \frac{\partial ln(S_{2008})}{\partial ln(S_t)}$
Q05	-0.024	0.902
Q10	-0.311	-0.243
Q15	-0.293	-0.171
Q20	-0.111	0.557
Q25	-0.147**	0.410**
Q30	-0.193***	0.227***
Q35	-0.187***	0.251***
Q40	-0.256***	-0.023***
Q45	-0.252***	-0.008***
Q50	-0.277***	-0.107***
Q55	-0.258***	-0.031***
Q60	-0.174***	0.303***
Q65	-0.128**	0.487**
Q70	-0.119*	0.523*
Q75	-0.040	0.838
Q80	-0.025	0.902
Q85	0.007	1.028
Q90	0.075	1.301
Q95	0.074	1.297

Notes: Wald-test for (1) H_0: $\frac{\partial y}{\partial ln(S_T)} = \beta_{ln(S_T)} + 2 \cdot \beta_{ln(S_T)^2} ln(S_T) = 0$ and (2) H_0: $\frac{\partial ln(S_{2008})}{\partial ln(S_t)} = 1 + A_{2008} \cdot g_S = 1$. Stars denote rejection: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: ZEW Spin-Off Survey 2008, author's calculations.

Another test of Gibrat's Law is based on the elasticity of end-of-period firm size with respect to beginning-of-period firm size. Gibrat's Law holds if a one percent increase in initial size gives rise to an increase in the end-of-period employment (here: employment in 2008) of one percent. The elasticity of end-of-period firm size with respect to beginning-of-period firm size is

$$E_S = \frac{\partial ln(S_{2008})}{\partial ln(S_t)} = 1 + A_{2008} \cdot \left[\beta_{ln(S_T)} + 2 \cdot \beta_{ln(S_T)^2} ln(S_T)\right] = 1 + A_{2008} \cdot g_S.$$

With a normalization of A_{2008} to 4 years, which is the median age in the sample, $E_S = -0.107$, which is significantly different from one. Hence, the null hypothesis that Gibrat's Law holds is rejected for employment growth of academic start-ups. Gibrat's Law fails to hold along almost the whole distribution. In fact, it can be rejected for all regressions from the 25 percent quantile up to the 70 percent quantile (see Table 3.4).

The year of foundation significantly influences annual employment growth. Growth rates are highest for firms founded in 2005, i.e. which have an age of three years. Their growth-rate is 7 percentage points higher at the median. With respect to the coefficient *founded in 2006* OLS and Median regression largely differ. Initial size is found to affect employment growth even in the lower quantiles, while the year of foundation only matters if the respective quantile includes growing firms (from the 40 percent quantile on).

Furthermore, coefficients composing the size-age-growth relationship vary sizeably from quantile to quantile when coefficients are compared along the growth distribution. Differences between the coefficient *log(size)* are statistically significant between the 60 percent quantile and the higher quantiles (see Figure 3.2). Moreover, almost all foundation year dummies differ significantly from quantile to quantile (see Figure 3.3). In addition, tests of equality of coefficients between the quantiles can be interpreted as a robust test of heteroscedasticity irrespective of the functional form of the heteroscedasticity (Cameron and Trivedi, 2009).

Table 3.5: Results of quantile regressions, selected quantiles

	Q5	Q10	Q25	Q40	Q50
Time-lag since academia was left(1)					
Still in science	-0.007	-0.000	-0.000	0.006	0.007
Time-lag: 3-5 years	0.001	0.000	-0.000	0.027**	0.040***
Time-lag: 6-10 years	0.005	-0.000	-0.000	0.017**	0.030**
Time-lag: 11-20 years	-0.004	-0.000	0.000	0.006	0.006
Time-lag: +20 years	-0.039*	0.000	-0.006*	-0.022***	-0.024**
(Spin-off)*(still in science)	-0.001	-0.029	-0.012	-0.028	-0.034*
(Spin-off)*(0-2 years)	-0.005	-0.000	-0.003	-0.030	-0.020
(Spin-off)*(3-5 years)	-0.057	0.000	-0.006	-0.028	-0.057*
(Spin-off)*(6-10 years)	-0.085**	-0.006	-0.009	-0.053***	-0.096***
(Spin-off)*(11-20 years)	0.012	-0.029	-0.013	-0.013	0.029
(Spin-off)*(+20 years)	0.046	0.000	0.003	-0.001	-0.019
Log(size)	-0.104***	-0.026	0.004	-0.002	-0.014
Log(size)^2	0.003	-0.012	-0.006**	-0.011***	-0.011***
Year of foundation(2)					
Founded in 2002	0.003	-0.000	-0.000	0.010	0.013*
Founded in 2003	-0.006	-0.000	-0.000	0.019***	0.026***
Founded in 2004	-0.003	0.000	-0.000	0.025***	0.040***
Founded in 2005	-0.010	-0.000	-0.000	0.036***	0.070***
Founded in 2006	0.001	0.000	-0.000	0.019**	0.049***
Innovation activities					
Continuous R&D	-0.002	-0.000	0.006	0.012	0.016*
Occasional R&D	-0.010	0.000	-0.000	0.002	-0.002
Market novelties	0.005	0.000	0.006	0.029***	0.036***
Science park	0.005	-0.000	0.059***	0.044***	0.029**
Public fund. (BA)	0.006	0.000	-0.000	-0.018***	-0.038***
Public fund. (non BA)	0.019**	0.000	0.018*	0.033***	0.033***
Limited liability	0.005	0.000	0.006	0.043***	0.053***
Exports	0.012*	-0.000	0.006	0.044***	0.057***
Team	0.038**	0.024**	0.003	0.007	0.004
No-expansion strategy	-0.013*	0.000	-0.006	-0.030***	-0.056***
Unemployed	-0.046	-0.024	-0.003	-0.014	-0.027
Contacts to academia					
Joint research	0.012	0.033	0.060***	0.015	-0.001
Contract research	0.013	0.024	0.007	0.007	-0.000
Customer	0.007	0.000	0.000	0.018*	0.018*
Continuing education	0.026	-0.000	0.006	0.037**	0.045***
Industry(3)					
High-tech manuf.	-0.001	0.000	0.003	0.015**	0.018**
Knowledge-int. serv.	-0.002	-0.000	-0.000	0.004	0.008
Constant	-0.011	-0.002	0.000	-0.001	0.031**
Pseudo R^2	0.146	0.044	0.011	0.094	0.113

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, based on bootstrapped standard errors with 500 replications. References: (1) start-up with time-lag: 0-2 years, (2) founded in 2001 (3) technology-intensive services. 4303 observations

Source: ZEW Spin-Off Survey 2008, author's calculations.

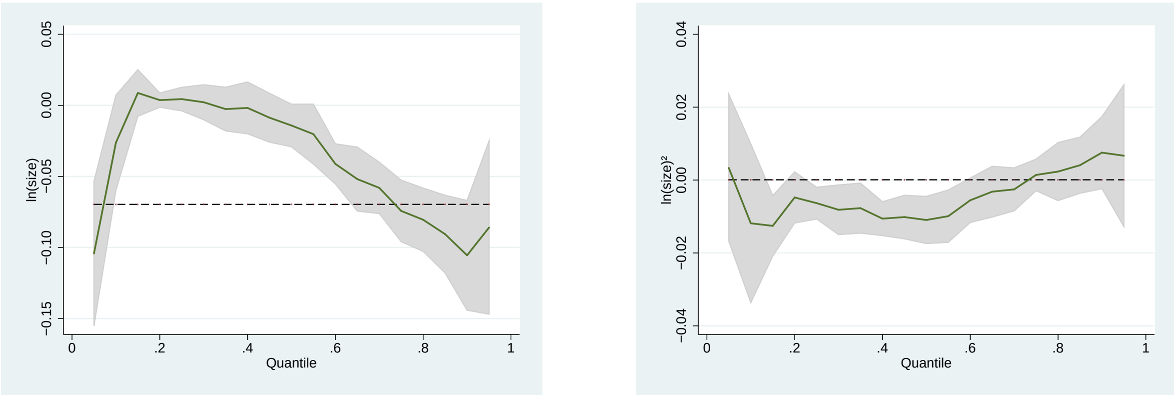
Table 3.5 – Continued

	Q60	Q70	Q75	Q80	Q90	Q95
Time-lag since academia was left(1)						
Still in science	0.003	0.007	0.016	0.012	0.021	0.024
Time-lag: 3-5 years	0.047***	0.047***	0.056***	0.057***	0.060***	0.070**
Time-lag: 6-10 years	0.023*	0.026**	0.036***	0.035**	0.042**	0.050*
Time-lag: 11-20 years	0.006	0.005	0.016	0.015	0.029*	0.038
Time-lag: +20 years	-0.034***	-0.040***	-0.026*	-0.030*	-0.021	-0.011
(Spin-off)*(still in sc.)	-0.043**	-0.056**	-0.062**	-0.039	-0.025	-0.056
(Spin-off)*(0-2 years)	-0.015	0.018	0.022	0.020	0.015	-0.003
(Spin-off)*(3-5 years)	-0.081*	-0.083*	-0.064	-0.085*	-0.097	-0.077
(Spin-off)*(6-10 years)	-0.092***	-0.111***	-0.098***	-0.101**	-0.065	-0.074
(Spin-off)*(11-20 years)	-0.001	-0.018	-0.016	-0.035	-0.004	-0.040
(Spin-off)*(+20 years)	0.014	0.027	0.030	0.028	0.087	0.040
Log(size)	-0.041***	-0.058***	-0.074***	-0.080***	-0.105***	-0.086***
Log(size)^2	-0.006*	-0.003	0.001	0.002	0.008	0.007
Year of foundation(2)						
Founded in 2002	0.018**	0.017*	0.017*	0.020*	0.029**	0.046**
Founded in 2003	0.041***	0.049***	0.057***	0.060***	0.070***	0.084***
Founded in 2004	0.061***	0.081***	0.091***	0.094***	0.124***	0.147***
Founded in 2005	0.113***	0.145***	0.160***	0.186***	0.248***	0.297***
Founded in 2006	0.119***	0.173***	0.193***	0.219***	0.363***	0.467***
Innovation activities						
Continuous R&D	0.030***	0.043***	0.038***	0.042***	0.036**	0.033
Occasional R&D	0.008	0.011	0.007	0.011	0.002	0.027
Market novelties	0.034***	0.029***	0.032***	0.031***	0.047***	0.059***
Science park	0.036**	0.029**	0.027*	0.013	0.026	0.038
Public fund. (BA)	-0.039***	-0.021	-0.022*	-0.033**	-0.038**	-0.038
Public fund. (non BA)	0.026***	0.026***	0.021**	0.022*	0.023	0.023
Limited liability	0.058***	0.057***	0.063***	0.063***	0.074***	0.088***
Exports	0.058***	0.062***	0.058***	0.063***	0.056***	0.065***
Team	-0.000	-0.007	-0.008	-0.006	-0.002	-0.022
No-expansion strategy	-0.067***	-0.060***	-0.063***	-0.074***	-0.083***	-0.081***
Unemployed	-0.058***	-0.071***	-0.079***	-0.085***	-0.128***	-0.119**
Contacts to academia						
Joint research	-0.013	-0.017	-0.004	-0.015	-0.028	-0.019
Contract research	-0.004	-0.008	-0.026	-0.044*	-0.026	-0.035
Customer	0.026*	0.024*	0.024	0.038*	0.047**	0.050
Continuing education	0.044**	0.065***	0.051***	0.043***	0.034	0.047
Industry(3)						
High-tech manuf.	0.025***	0.021**	0.024**	0.019*	0.010	0.016
Knowledge-int. serv.	0.022***	0.019**	0.019**	0.020**	0.013	0.019
Constant	0.067***	0.108***	0.128***	0.157***	0.219***	0.231***
Pseudo R^2	0.124	0.141	0.150	0.163	0.201	0.239

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, based on bootstrapped standard errors with 500 replications. References: (1) start-up with time-lag: 0-2 years, (2) founded in 2001 (3) technology-intensive services. 4303 observations

Source: ZEW Spin-Off Survey 2008, author's calculations.

Homoscedasticity of the data can therefore be rejected. Initial size and age do not only affect the location of the distribution of firms' employment growth but also the scale.



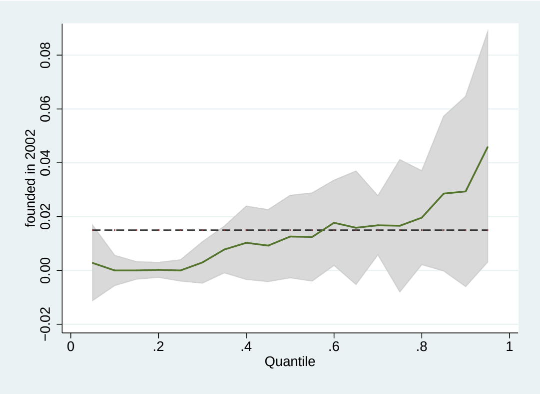
(a) $log(size)$ (b) $log(size)^2$

Figure 3.2: Variation in the coefficients of initial firm size

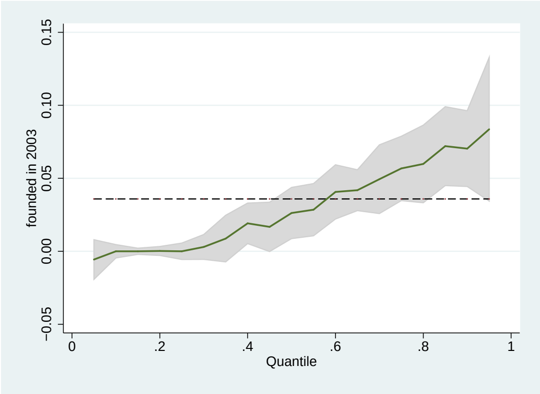
Note: Horizontal lines represent OLS estimates, solid lines and shaded areas represent quantile regression estimates with 95% confidence intervals.
Source: ZEW Spin-Off Survey 2008, author's calculations.

Innovation activities in terms of continuous R&D and the introduction of market novelties enhance median firm's employment growth by about 2 and 4 percent, respectively. However, innovation activities can only foster employment growth if the firm is reasonably healthy. For non-growing firms (5, 10 and 25 percent quantiles), all coefficients measuring innovation activities are insignificant. While the effect of market novelties does not differ significantly among the quantiles, *continuous R&D* differs significantly between the 50 percent quantile and the quantiles above.

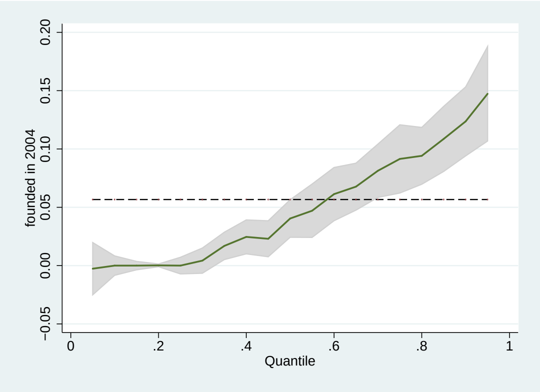
Public support in terms of being hosted in a science park or receiving public funds is found to spur employment growth substantially. However, the differentiation between funding from the Federal Employment Agency *(public funding (BA))* and other public agencies *(public funding (non BA))* has been pointed out to be pretty important. For funding from the Federal Employment Agency, poor growth prospects of start-ups by the unemployed prevails. One may assume that the small volume of BA-funding does not ease financial constraints substantially. In contrast, other public funding seems to relax financial constraints and help firms to realize their growth potentials. For these firms, employment growth is about 3 percent higher (median regression).



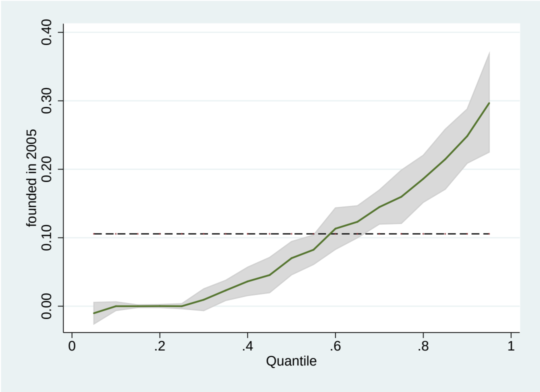
(a) Founded in 2002



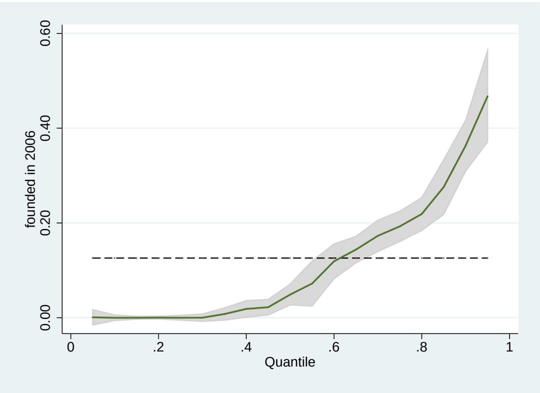
(b) Founded in 2003



(c) Founded in 2004



(d) Founded in 2005



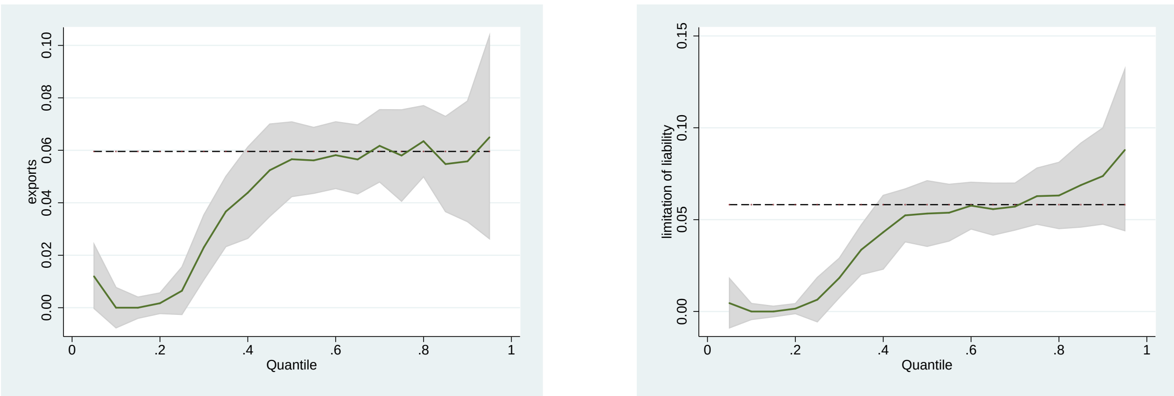
(e) Founded in 2006

Figure 3.3: Variation in the coefficients of the year of foundation

Note: Horizontal lines represent OLS estimates, solid lines and shaded areas represent quantile regression estimates with 95% confidence intervals.
Source: ZEW Spin-Off Survey 2008, author's calculations.

The same is true for being located in a science park (median growth is about 3 percent higher). Since the usage of infrastructure at low or zero cost mainly helps start-ups in very early stages, it is not surprising that the variable *science park* reveals the highest effect at the 25 percent quantile (growth increases by 6 percent) compared to an important, but significantly smaller effect at the 75 percent quantile (growth increases by 3 percent). But this effect should be interpreted cautiously since the growth performance of start-ups hosted by a science park can be driven by a "picking the winners" selection process of the managers of science parks.

Positive effects of exporting activities on firm growth, which have been found in earlier empirical literature, can be attested by this study, too. The median firm exhibits a 6 percent gain in employment growth when carrying out exporting activities. The effect of exporting on academic start-up's employment growth is furthermore significantly increasing from the 30 percent quantile to the 50 percent quantile (see Figure 3.4).



(a) Exporting (b) Limitation of liability

Figure 3.4: Variation in the coefficients *exports* and *limited liability*

Note: Horizontal lines represent OLS estimates, solid lines and shaded areas represent quantile regression estimates with 95% confidence intervals.
Source: ZEW Spin-Off Survey 2008, author's calculations.

A limitation of liability exerts a positive stimulus on employment growth. This effect is significantly growing from a 4 percent stimulus at the 25 percent quantile up to a 9 percent stimulus at the 95 percent quantile (see Figure 3.4). On the contrary, starting the venture in a team of founders is only relevant for firms of the lower growth quantiles. The team dummy is only significant in the regressions for the 5 and 10 percent quantiles.

Controlling regressors for firm strategies which are not growth-oriented, industry effects, and longer unemployment spells during the time after academia provide the expected effects. For firms having a no-expansion strategy, not only the location but also the scale of start-up's employment growth is found to be considerably affected. The coefficient *no-expansion strategy* is steadily decreasing along the quantiles (see Figure 3.5).

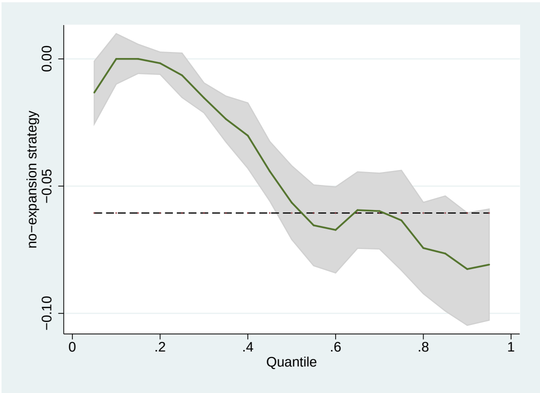


Figure 3.5: Variation in the coefficient *no-expansion strategy*

Note: Horizontal lines represent OLS estimates, solid lines and shaded areas represent quantile regression estimates with 95% confidence intervals.
Source: ZEW Spin-Off Survey 2008, author's calculations.

Positive effects of academic networks can only be found if academia is a firm's customer or if the firm's employees have received advanced training in academia. This reveals that not only the human capital of the founders is important for academic start-up's firm success but also the human capital of its employees.

In order to test the robustness of the results, a set of further median regressions was conducted. In each case a different set of control variables was excluded. The results remain stable (see Table 3.7 in the Appendix). Some coefficients get larger if the variables *limitated liability*, *exports*, *team*, *no-expansion strategy* and *unemployed* are excluded. This result is reasonable since most of these coefficients have been shown to exert important influence on employment growth.

3.5 Conclusions

This chapter has investigated the human capital depreciation of entrepreneur's academic knowledge. As the influence of a potential knowledge depreciation on firms employment growth ought to be studied, the analysis has been conducted on the firm level. Examining employment growth is also beneficial since further insights in young firms' labor demand are gained.

Using quantile regressions, I find a rapid decline of academic knowledge after an academic institution is left. Professional experience, which is gained at the same time, overcompensates the losses in academic knowledge up to a certain point in time. The highest growth rates are found for new firms with a founding time-lag of 3-5 years after academia has been left. Thus, for launching an ordinary academic start-up it is best to acquire 3-5 years of professional experience before starting an own venture. This result should be taken into consideration by policy makers when designing policy programs which aim to encourage students to become self-employed. If substantial technology transfer is involved in launching the start-up, as it is the case for academic spin-offs, depreciation of academic knowledge is of a higher importance. The danger of obsolescence of academic knowledge and catching-up of others makes it most advantageous to start the firm directly, i.e. with a time-lag of up to two years, after the university has been left. Starting the venture while at least one of the founder is still in academia is not advantageous for academic spin-offs since common effort of *all* founders is needed in the early stages of firm's development.

Furthermore, the determinants of academic start-up's employment growth are examined along the whole distribution of young firms' employment growth. Some factors, e.g. founding in a team of founders or having been hosted in a science park, are of higher relevance for firms in the lower part of the growth distribution, while other prominent factors, such as exporting, continuous R&D, and a limited liability, are most important for high-growing firms.

Gibrat's Law, stating that the size of a firm and its growth rate are independent, can be rejected along wide parts of the distribution of young firms' employment growth. This result is a material contribution to the literature of young firms' growth since the validity of Gibrat's Law was mainly tested in the conditional mean framework.

3.A Appendix

3.A1 Description of variables

Table 3.6: Definition and descriptive statistics of all variables

Variable	Definition	Mean	Std. dev.
Time-lag since academia was left			
Still in science	At the time of establishment one of the founders was still in science (Dummy)	0.170	(0.375)
Time-lag: 0-2 years	The (last) founder left academia 0-2 years before founding (Reference category)	0.101	(0.302)
Time-lag: 3-5 years	The (last) founder left academia 3-5 years before founding (Dummy)	0.115	(0.319)
Time-lag: 6-10 years	The (last) founder left academia 6-10 years before founding (Dummy)	0.179	(0.384)
Time-lag: 11-20 years	The (last) founder left academia 11-20 years before founding (Dummy)	0.260	(0.439)
Time-lag: +20 years	The (last) founder left academia more than 20 years before founding (Dummy)	0.174	(0.379)
(Spin-off)*(still in sc.)	Interaction: academic spin-off (Dummy) still in science (Dummy)	0.021	(0.143)
(Spin-off)*(0-2 years)	Interaction: academic spin-off (Dummy) with time-lag: 0-2 years (Dummy)	0.013	(0.112)
(Spin-off)*(3-5 years)	Interaction: academic spin-off (Dummy) with time-lag: 3-5 years (Dummy)	0.007	(0.083)
(Spin-off)*(6-10 years)	Interaction: academic spin-off (Dummy) with time-lag: 6-10 years (Dummy)	0.009	(0.095)
(Spin-off)*(11-20 years)	Interaction: academic spin-off (Dummy) with time-lag: 11-20 years (Dummy)	0.011	(0.103)
(Spin-off)*(+20 years)	Interaction: academic spin-off (Dummy) with time-lag: +20 years (Dummy)	0.010	(0.097)
Log(size)	Logarithm of initial employment	0.859	(0.840)
Log(size)^2	Logarithm of initial employment squared	1.444	(2.329)
Year of foundation			
Founded in 2001	Start-up was founded in 2001 (Ref. cat.)	0.151	(0.358)
Founded in 2002	Start-up was founded in 2002 (Dummy)	0.153	(0.360)
Founded in 2003	Start-up was founded in 2003 (Dummy)	0.179	(0.384)
Founded in 2004	Start-up was founded in 2004 (Dummy)	0.176	(0.381)
Founded in 2005	Start-up was founded in 2005 (Dummy)	0.185	(0.388)
Founded in 2006	Start-up was founded in 2006 (Dummy)	0.156	(0.363)
Innovation activities			
Continuous R&D	Firm conducts continuous R&D (Dummy)	0.220	(0.415)
Occasional R&D	Firm conducts occasional R&D (Dummy)	0.128	(0.334)
Market novelties	Introduction of products new to the market (Dummy)	0.299	(0.458)

Continued on next page...

Table 3.6 – Continued

Variable	Definition	Mean	Std. dev.
Public support			
Science park	Firm has been hosted by a science park or business incubator (Dummy)	0.059	(0.237)
Public funding (BA)	Firm has received funding from the Federal Employment Agency (Dummy)	0.095	(0.293)
Public funding (non BA)	Firm has received funding from other public agencies (Dummy)	0.156	(0.363)
Other firm and founder specific variables			
Limited liability	Legal form of the company involves limited liability for its owners (Dummy)	0.547	(0.498)
Exports	Firm sells its products or services (also) abroad (Dummy)	0.461	(0.499)
Team	Establishment has taken place in a team of founders (Dummy)	0.359	(0.480)
No-expansion strategy	Firm is not growth-oriented (Dummy)	0.344	(0.475)
Unemployed	Founder(s) have had a longer unemployment spell between academia and firm foundation (Dummy)	0.012	(0.109)
Contacts to academia			
Joint research	Firm has regular contacts with academia in the form of joint research (Dummy)	0.049	(0.216)
Contract research	Firm has regular contacts with academia in the form of contract research (Dummy)	0.021	(0.143)
Customer	Firm has regular contacts with academia in the form of customers (Dummy)	0.070	(0.255)
Cont. education	Firm has regular contacts with academia in the form of continuing education of firm's employees (Dummy)	0.048	(0.214)
Industries			
High-tech manufact.	Industry: High-technology manufacturing (Dummy)	0.241	(0.428)
Knowledge-intensive serv.	Industry: Knowledge-intensive services (Dummy)	0.405	(0.491)
Technology-int. serv.	Industry: Technology-intensive services (Reference category)	0.353	(0.478)

Source: ZEW Spin-Off Survey 2008, author's calculations.

3.A2 Robustness check

Table 3.7: Robustness-checks: Median regressions on employment growth

	Q50 (1)		Q50(2)	
	coeff.	se	coeff.	se
Time-lag since academia was left[1]				
Still in science	0.004	(0.010)	-0.000	(0.012)
Time-lag: 3-5 years	0.036**	(0.014)	0.038**	(0.016)
Time-lag: 6-10 years	0.025**	(0.011)	0.022*	(0.013)
Time-lag: 11-20 years	0.008	(0.010)	0.002	(0.010)
Time-lag: +20 years	-0.024**	(0.011)	-0.029**	(0.012)
(Spin-off)*(still in science)			-0.035**	(0.017)
(Spin-off)*(0-2 years)			-0.028	(0.026)
(Spin-off)*(3-5 years)			-0.053*	(0.030)
(Spin-off)*(6-10 years)			-0.098***	(0.033)
(Spin-off)*(11-20 years)			0.016	(0.029)
(Spin-off)*(+20 years)			-0.002	(0.052)
Log(size)	-0.016	(0.010)	-0.013	(0.010)
Log(size)^2	-0.010***	(0.003)	-0.011***	(0.003)
Year of foundation$^{(2)}$				
Founded in 2002	0.012	(0.007)	0.008	(0.007)
Founded in 2003	0.024***	(0.008)	0.023***	(0.009)
Founded in 2004	0.038***	(0.009)	0.037***	(0.009)
Founded in 2005	0.068***	(0.012)	0.066***	(0.010)
Founded in 2006	0.048***	(0.014)	0.042***	(0.014)
Innovation activities				
Continuous R&D	0.016*	(0.009)		
Occasional R&D	-0.006	(0.010)		
Market novelties	0.036***	(0.008)		
Science park	0.024*	(0.012)	0.039***	(0.014)
Public funding (BA)	-0.037***	(0.010)	-0.037***	(0.010)
Public funding (non BA)	0.031***	(0.008)	0.029***	(0.008)
Limited liability	0.054***	(0.008)	0.056***	(0.008)
Exports	0.056***	(0.007)	0.062***	(0.007)
Team	0.005	(0.008)	0.003	(0.007)
No-expansion strategy	-0.056***	(0.007)	-0.059***	(0.007)
Unemployed	-0.020	(0.018)	-0.032*	(0.019)
Contacts to academia				
Joint research	0.003	(0.017)	0.019	(0.013)
Contract research	-0.000	(0.021)	0.004	(0.020)
Customer	0.014	(0.012)	0.019*	(0.011)
Continuing education	0.047***	(0.014)	0.045***	(0.013)
Industry$^{(3)}$				
High-tech manuf.	0.018**	(0.009)	0.025***	(0.008)
Knowledge-int. serv.	0.010	(0.007)	0.011	(0.007)
Constant	0.033***	(0.012)	0.046***	(0.013)
Observations	4303		4322	
Pseudo R^2	0.111		0.107	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, bootstrapped standard errors (500 replications) in parentheses. References: (1) time-lag: 0-2 years, (2) founded in 2001, (3) technology-intensive services.

Source: ZEW Spin-Off Survey 2008, author's calculations.

Table 3.7 – Continued

	Q50(3)		Q50(4)		Q50(5)	
	coeff.	se	coeff.	se	coeff.	se
Time-lag since academia was left[1]						
Still in science	0.000	(0.011)	-0.004	(0.012)	0.011	(0.011)
Time-lag: 3-5 years	0.032**	(0.014)	0.060***	(0.015)	0.042***	(0.014)
Time-lag: 6-10 years	0.023*	(0.012)	0.039***	(0.013)	0.032***	(0.012)
Time-lag: 11-20 years	0.001	(0.011)	0.011	(0.011)	0.009	(0.010)
Time-lag: +20 years	-0.028**	(0.012)	-0.032***	(0.011)	-0.020*	(0.012)
(Spin-off)*(still in sc.)	-0.031	(0.020)	-0.020	(0.026)	-0.025	(0.018)
(Spin-off)*(0-2 years)	-0.011	(0.027)	-0.004	(0.034)	-0.016	(0.035)
(Spin-off)*(3-5 years)	-0.071**	(0.031)	-0.067	(0.042)	-0.063**	(0.029)
(Spin-off)*(6-10 years)	-0.099***	(0.031)	-0.082***	(0.026)	-0.091***	(0.030)
(Spin-off)*(11-20 years)	0.021	(0.028)	-0.028	(0.045)	0.020	(0.028)
(Spin-off)*(+20 years)	-0.016	(0.040)	-0.004	(0.035)	-0.023	(0.041)
Log(size)	-0.009	(0.010)	0.031***	(0.012)	-0.014	(0.010)
Log(size)^2	-0.012***	(0.003)	-0.018***	(0.004)	-0.011***	(0.003)
Year of foundation$^{(2)}$						
Founded in 2002	0.010	(0.007)	0.005	(0.007)	0.014*	(0.007)
Founded in 2003	0.021**	(0.008)	0.025***	(0.009)	0.027***	(0.008)
Founded in 2004	0.035***	(0.009)	0.036***	(0.012)	0.038***	(0.009)
Founded in 2005	0.065***	(0.011)	0.068***	(0.016)	0.071***	(0.012)
Founded in 2006	0.039***	(0.014)	0.043**	(0.019)	0.048***	(0.015)
Innovation activities						
Continuous R&D	0.019**	(0.008)	0.046***	(0.010)	0.021**	(0.010)
Occasional R&D	-0.000	(0.009)	0.020**	(0.010)	0.003	(0.009)
Market novelties	0.033***	(0.008)	0.056***	(0.010)	0.036***	(0.007)
Science park			0.052***	(0.012)	0.036***	(0.013)
Public fund. (BA)			-0.040***	(0.010)	-0.039***	(0.010)
Public fund. (non BA)			0.040***	(0.009)	0.032***	(0.008)
Limited liability	0.055***	(0.009)			0.054***	(0.008)
Exports	0.060***	(0.007)			0.056***	(0.007)
Team	0.004	(0.008)			0.004	(0.008)
No-expansion strategy	-0.060***	(0.007)			-0.057***	(0.007)
Unemployed	-0.030	(0.021)			-0.025	(0.020)
Contacts to academia						
Joint research	0.011	(0.015)	-0.002	(0.017)		
Contract research	-0.003	(0.019)	0.022	(0.025)		
Customer	0.014	(0.011)	0.018	(0.014)		
Continuing education	0.047***	(0.014)	0.055***	(0.019)		
Industry$^{(3)}$						
High-tech manuf.	0.025***	(0.009)	0.035***	(0.009)	0.020**	(0.008)
Knowledge-int. serv.	0.011*	(0.007)	0.025***	(0.009)	0.009	(0.007)
Constant	0.039***	(0.013)	0.004	(0.011)	0.030**	(0.012)
Observations	4308		4321		4303	
Pseudo R^2	0.108		0.073		0.111	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, bootstrapped standard errors (500 replications) in parentheses. References: (1) time-lag: 0-2 years, (2) founded in 2001, (3) technology-intensive services.

Source: ZEW Spin-Off Survey 2008, author's calculations.

4 Entry strategies, human capital, and start-up size

4.1 Introduction

One of the stylized facts of entry we know is that new firms are typically small. Furthermore, the firm size distribution of new firms is mostly positively skewed.
Since the results of many studies indicate that initial founding conditions matter for firm success, it is desirable to get a better understanding of firms' start-up size. More precisely, the probability of survival is positively related to the initial firm size (see Audretsch and Mahmood, 1995). Furthermore, start-up size seems to have a rather persistent effect on survival (Geroski et al., 2007). Since most studies testing Gibrat's Law for young firms (e.g. Lotti et al., 2009; Almus and Nerlinger, 1999, 2000) arrive at a rejection of it, not only survival, but also firm growth, is substantially influenced by start-up size.

Theoretically, a firm's start-up size is determined by the minimum of its optimal initial size and the entrepreneurs' resource constraints. Factors influencing either the optimal initial size or entrepreneurs' resource constraints will therefore have an impact on the actual initial size.
Empirical research on the determinants of start-up size is rather limited. Only a few empirical studies have built the basis about the facts we know today. Since optimal firm size is largely determined by the extent of economies of scale in the industry, most of these studies focus on industry characteristics (Resende, 2007; Mata and Machado, 1996; Arauzo-Carod and Segarra-Blasco, 2005). They find that a firm's start-up size is positively influenced by minimum efficient scale, industry growth, and turbulence inside the industry.

However, optimal initial size may not only be influenced by industry characteristics but also by founders' abilities and entry strategies. Founders' uncertainty about their true entrepreneurial abilities, combined with the existence of sunk costs, is another reason why firms may choose to start small (Mata, 1996). The belief in one's own entrepreneurial competence is linked to human capital. Individuals with a higher amount of human capital are likely to perform better than other entrepreneurs. As a conse-

quence, they should be more confident about the future prospects of their firm and desire a higher initial size. Because human capital increases the expected efficiency of a firm, it should increase the start-up size, too. Furthermore, it might be easier for more educated and experienced founders to hire qualified personnel and to find suitable team members.
Studies which control for human capital or explicitly investigate the influence of entrepreneurs' human capital are rare (Colombo et al., 2004; Mata, 1996; Barkham, 1994), and to the best of our knowledge there are still none for Germany. Mata (1996) and Colombo et al. (2004) find a crucial positive influence of entrepreneurs' human capital on start-up size. Better educated founders are not only more likely to be efficient managers, they are also assumed to be wealthier individuals. Hence, they suffer less from financial constraints. Using entrepreneur's age and educational level as proxies for wealth, Cabral and Mata (2003) find a significant influence on a firm's size in early years.

We extend the framework of the determinants of start-up size by introducing entry strategies as an important determinant of initial size. The choice of a particular entry strategy can have both an influence on the optimal initial size and the ability to assemble resources. Using information on the firms' activities in research and development and on the major motive for firm formation, we distinguish different types of entry strategies, namely entry based on innovation, opportunity entrepreneurship, necessity entrepreneurship, independency entrepreneurship, and spin-out entrepreneurship.
Objectives about future innovativeness, measured by the leading decision to be active in research and development (R&D), force a firm to take high investments in technologies and personnel in order to realize their R&D projects. Furthermore, different motivations why to start a firm are accompanied by diverse entry strategies. For example, firm foundations based on a market opportunity are expected to have better prospects than firm foundations driven by necessity. Consequently, the optimal initial size will be higher and resource constraints will be smaller in case of opportunity entrepreneurship.

We further contribute to the literature by conducting the first study about firm's start-up size for Germany. We analyze the role of founders' human capital and industry characteristics on initial firm size based on a large sample of newly established firms in almost all industries. We are able to distinguish between generic and specific human capital. Generic human capital refers to the general knowledge acquired through formal education and professional experience. Specific human capital comprises competencies which can be directly applied to the entrepreneurial job. Concerning entrepreneurial experience, we distinguish between successful and unsuccessful self-employment which has not been done before.

Our empirical analysis is based on a newly generated and unique database in Germany, which contains around 5,000 firms established in the years 2005 to 2007. The industries cover manufacturing and services and include both high-tech and low-tech sectors. Information about a founder's human capital, firm characteristics, and market entry strategies was retrieved using computer-assisted telephone interviews. As we include only very young firms (up to an age of three years) in our analysis we are hardly exposed to a survival bias of the surveyed firms.

Like many similar studies, we measure start-up size by the number of employees and founders when the firm is created. While other studies approximate initial size by firm size twelve or even 36 months after start-up, we are able to measure the size exactly at the point in time when the start-up is created. Furthermore, we are not restricted to firms with at least one employee since we have information about firms which have created only jobs for the founder(s). More specifically, start-up size is measured both in full-time equivalents and in head counts. Since workload in extremely young firms is rather volatile and employees have to be highly flexible, the number of individuals engaged in a firm may be more important than formal working hours agreed in work contracts. Start-up size is explained by market entry strategies as well as by an entrepreneur's human capital. Since previous studies have provided some evidence for the importance of industry characteristics in determining a firm's initial scale, we also include industry variables in our analysis.

Our regression results show that the inclusion of variables intended to capture entry strategies help substantially to explain the heterogeneity in start-up size. We further find that both generic human capital, such as the formal educational degree of the founders, and specific human capital, such as successful entrepreneurship, is positively related to a firm's start-up size. All in all, our results show that it is important to account for founder-specific, firm-specific, and industry-specific factors in order to better understand the size distribution of new-born firms.

In the next section, we give an overview of the empirical literature on start-up size. In the subsequent part, we derive hypotheses concerning the effect of firm's entry strategy, the founder's human capital, and industry characteristics on start-up size. In the empirical part, we describe the econometric model, the data and variables used and the empirical findings. We give a summary of our results in the final section.

4.2 Literature review

Although it is well-known that a firm's initial size has a crucial influence on its performance in the years following market entry (see Audretsch and Mahmood, 1995; Geroski et al., 2007), not that much empirical work has been done which investigates the determinants of a firm's size at its founding date.

Theoretically, firm's initial size is determined by the minimum of its optimal initial size and founders' (financial) constraints (Cabral and Mata, 2003). Most of the somewhat rare empirical studies which investigate the determinants of start-up size concentrate on industry characteristics (Resende, 2007; Arauzo-Carod and Segarra-Blasco, 2005; Görg et al., 2000; Görg and Strobl, 2002; Mata and Machado, 1996). This is presumably due to lack of detailed information about founders in firm-level data. Based on a first study by Mata and Machado (1996) these studies relate start-up size to the minimum efficient scale (MES) in the respective industry, the proportion of employment in that industry that is employed in firms operating below the MES, the size of the industry, the growth of the industry, and the extent of simultaneous entry and exit (turbulence) in the industry. MES and turbulence are found to have a significant positive influence. Industry growth is often found to be also positively related to start-up size, but not always in a significant way. The other way around, as expected, the proportion of employment in an industry working at suboptimal scale exerts a negative influence on start-up size. Industry size is mostly expected to have a positive influence on start-up size, but it often turns out to be insignificant in empirical studies. In fact, it is found to have a significant negative effect in some studies (e.g. Resende, 2007).

Quantile regressions of this type of studies show that scale economies are more important the larger the entrant. "[I]t seems that small new firms appear everywhere, while relatively large ones only appear where economies of scale make it crucial [. . .]" (Mata and Machado, 1996, p. 1321).

One of the first studies which does not solely focus on industry characteristics but takes the influence of entrepreneur's attributes into account when analyzing the size of new firms, was done by Mata (1996). He finds education, measured by the years of schooling, to positively influence start-up size. The relationship of initial size and a founder's age, which is supposed to be a proxy for labor market experience after controlling for education, is found to be inversely u-shaped. Mata therefore concludes that the size of new firms increases with an entrepreneur's human capital.

Barkham (1994) investigates the effect of entrepreneurial characteristics on the size of new firms in the UK. He measures size by total assets, turnover, and total employment at the end of the third year of trading. For total employment, he finds a positive effect of a high motivation of the founders and of having managerial skills.

Colombo et al. (2004) explicitly focus on the influence of an entrepreneur's human capital on firms' start-up size. Following Becker (1993), they distinguish between generic and specific human capital. From theoretical reasoning, they draw the hypothesis that firms' start-up size is positively related to the human capital of a firm's founders. First, imperfections in capital markets may lead to financial constraints which force the founders to start below their optimal start-up size. Human capital, independently of its specific or generic nature, usually comes along with a higher personal wealth and less exposure to financial constraints. Therefore, founders with greater human capital can achieve their optimal initial firm size more easily. Second, the specific human capital of a founder will be positively related to his entrepreneurial ability, his confidence in the firm's post-entry performance, and hence to the optimal initial size. According to this reasoning, the generic human capital component is first and foremost a proxy for wealth, while the specific component also captures founders' greater entrepreneurial ability and self-confidence. Consequently, Colombo et al. (2004) claim the impact of specific human capital on initial firm size to be greater than that of generic human capital. Controlling also for industry-specific influences on initial firm size, they find their hypothesis to be confirmed. Both specific human capital, which is captured by industry-specific working experience, entrepreneurial and managerial experience, and generic human capital, which is proxied by education and general working experience, positively influence a firm's start-up size as measured by the salaried employees (plus founders) twelve months after the firm has started to operate. The variables reflecting the specific component of human capital are found to exhibit greater explanatory power than those reflecting the generic component.

Carrasco (1999) investigates the decision to enter self-employment without and with employees. Probabilities of entry are found to be higher the more educated the individual is. The positive effect is even larger for entering self-employment with employees. Furthermore, financial constraints are of special relevance when entering self-employment with employees. Similarly, Congregado et al. (2008) find a positive effect of wealth variables on the transition probability from paid employment to self-employment with employees, but not for becoming own-account workers.

Astebro and Bernhardt (2005) analyze the impact of various human capital variables on the start-up capital of firms which can be considered as an alternative measure of initial firm size. They find that firm capital is generally increasing with human capital. Similar to the results of Colombo et al. (2004), the effects of variables reflecting specific human capital (here: entrepreneurial ability, managerial experience) are larger in magnitude than the effects of variables reflecting generic human capital (here: education and work experience).

To the best of our knowledge, apart from Barkham (1994), who investigates the influence of highly growth-motivated founders on start-up size, entry strategies have not been investigated as determinants of start-up size.

4.3 Determinants of start-up size

In deriving our hypotheses, we build on the framework developed by Cabral and Mata (2003) and Colombo et al. (2004) which perceives initial size as being determined by the optimal initial size and resource constraints the start-up is faced with. Initial size (s_i^0) is given by $s_i^0 = \min[s_i^*, w_i]$, with s_i^* being the optimal initial size and w_i being the available resources. The optimal initial size s_i^* is derived by maximizing the founder's expected earnings, which are determined by industry characteristics and each firm's efficiency. A new firm's efficiency is assumed to be primarily affected by the human capital of the founders. Also, the resources are largely determined by a founder's human capital since personal wealth is usually positively correlated with human capital.

All factors influencing either the optimal initial size or the available resources thus determine the start-up size. We extend the model by arguing that expected earnings and available resources are not only influenced by industry characteristics and founders' human capital but also by the motivations of the founders to start a business and their respective entry strategies. Therefore, we focus on three particular groups of factors which presumably influence start-up size: the firm's entry strategy, the founder's human capital, and industry characteristics.

Entry strategies are expected to have a crucial influence on optimal initial size. We distinguish different types of entry strategies. The first entry strategy we discuss is based on the objective to serve the market with innovative products. Firms which conduct research and development continuously are most likely to be able to introduce innovative products in the future. The leading decision to be active in research and development forces the start-up to take high investments in technologies and (especially high-qualified) personnel in order to realize their R&D projects and maximize their profits. Therefore, start-ups which have made the leading decision to be active in R&D are hypothesized to have a larger initial size.

Entry is furthermore classified according to the main motive of the founder for firm formation. Entrepreneurial motivation has been also claimed to have an important impact on firm size by Barkham (1994). Motivation determines the ability of entrepreneurs to assemble resources. Highly motivated founders will thus be less restricted to obtain external finance. Furthermore, highly motivated founders might be less reluctant to direct a larger firm because they are willing to accept the stress associated with managing a bigger firm and because they are more confident of their own abilities. On the basis of different motives, we distinguish four main groups of entry strategies, namely, opportunity entrepreneurship, necessity entrepreneurship, independency entrepreneurship, and spin-out entrepreneurship. According to the Global Entrepreneurship Monitor (GEM), opportunity entrepreneurship refers to the motivation of taking advantage of a business opportunity while necessity entrepreneurship refers to new ventures which are started because there have been no better choices for work (Reynolds et al., 2005).

Due to poor job market opportunities, the opportunity costs of self-employment should be lower for necessity entrepreneurs than for opportunity entrepreneurs. Thus, the present value of the expected stream of income on which necessity entrepreneurs decide to go self-employed should be lower, too (see Pfeiffer and Reize, 2000). Furthermore, these founders often prefer to work as paid-employed rather than being self-employed and thus often regard self-employment as a temporary state. This reasoning is backed by the finding that necessity entrepreneurs are less satisfied with their start-up (Block and Koellinger, 2009). It is then rational for them to keep sunk costs low and to enter at small scale. They are presumably first and foremost interested in creating a job for themselves and in ensuring a certain income level. Their entrepreneurial aspirations and their willingness to take major investments can be assumed to be rather low (Niefert and Tchouvakhina, 2006). Consequently, we expect that start-ups driven by necessity will have a smaller initial size than others.

Opportunity entrepreneurship exists if the firm is founded due to a precise business idea or an opened-up market gap. On average, these entrepreneurs should be more convinced of their business idea than the average entrepreneur. They expect the present value of future earnings to be higher and consequently dare to take higher risk. Therefore, initial investments will be larger. One may further argue that a lot of these foundations will also follow an innovation strategy because the probability to develop a market novelty in the first years after foundation has been found to be higher among foundations based on a precise business idea than among other new firms (Gottschalk et al., 2008).

If the founders are mainly driven by the motive to work self-determined and independently, one can refer to this strategy as independency entrepreneurship. Profit maximization and growth is mostly not the prior objective of those founders since "being one's own boss" provides non-pecuniary benefits to self-employed persons (Benz and Frey, 2004). They are mainly out to build up an economically viable business in order to earn their living. Since employing personnel requires managerial capacities and the engagement of managerial staff, start-ups driven by independency entrepreneurship might prefer to start at a smaller scale and therefore restrict themselves to a smaller initial size.

Spin-out entrepreneurship is defined as a firm formation which originates from previous activities in dependent employment. Common definitions of corporate spin-outs refer to entrepreneurial ventures by ex-employees of an incumbent firm to corporate spin-outs (e.g. Agarwal et al., 2004; Klepper and Sleeper, 2005). Spin-outs are "entries whose impetus originates from within an existing company" (Eriksson and Kuhn, 2006, p.1022). In the present study we employ a narrower concept of spin-out entrepreneurship and refer only to those firms as spin-outs which are pushed by the founders' former employers (Tübke, 2004).[1] We expect that these firms, just as the foundations by opportunity en-

[1]Bünstorf (2007) calls corporate spin-outs which are triggered by push-factors "necessity spin-outs". Further expressions found in the literature are push spin-offs, passive spin-offs or restructuring-driven spin-offs (see Tübke, 2004).

trepreneurs, start their business following a precise plan. A founder's previous employer may serve as a source of market information necessary for firm formation (Barkham, 1994). Furthermore, knowledge-transfer and knowledge-exploitation might take place from the parent firm (Helfat and Lieberman, 2002; Klepper and Sleeper, 2005). The founders should be rather confident about the sustainability of the business idea because they probably have insider knowledge about the corresponding market and are already experienced in the field the new firm is operating in. Thus, expected earnings and optimal initial size increase. Additionally, resource constraints should be less severe since firm formation was pushed by the former employer who might be able to support the founders with valuable management advice during seed stage. They might even receive financial assistance or take over qualified personnel from their former employer.[2] To sum up, our hypotheses about entry strategies are as follows:

Hypothesis 1a: *Entry which aims to serve the market with innovative products occurs at a larger scale.*
Hypothesis 1b: *Firm foundations based on opportunity entrepreneurship and spin-out entrepreneurship start larger than independency entrepreneurship and necessity entrepreneurship where necessity entrepreneurship exhibits even a smaller start-up size than independency entrepreneurship.*

The founders' human capital is presumed to exert a positive influence on start-up size for several reasons. First, human capital will affect entrepreneurial success. Founders' human capital will largely determine the business idea and the type of products and services a firm offers. This will in turn impact entrepreneurial outcomes. Entrepreneurial performance has been shown to be largely influenced by the generic human capital, e.g. the type of schooling and years of schooling (Van der Sluis et al., 2008). The importance of human capital for entrepreneurial outcomes is usually found to be substantial. Estimations on returns to education even show that both returns to education and returns to social abilities are significantly higher for entrepreneurs than for employees (Van Praag, 2006). Since both generic and specific human capital have a positive impact on future performance (Colombo and Grilli, 2005b; Bosma et al., 2004; Koeller and Lechler, 2006), the present value of expected entrepreneurial earnings and optimal initial size increase with the level of human capital.

[2] Eriksson and Kuhn (2006) use a definition for corporate spin-outs which is based on employee mobility from the parent firm.

However, generic and specific human capital is assumed to affect the efficiency of the firm differently. Persons endowed with specific human capital, i.e. knowledge and skills which can be directly applied to entrepreneurial tasks, are more likely to identify and pursuit opportunities and to be efficient managers (Van Praag, 2006). They are also supposed to have greater confidence in their entrepreneurial success and to assess failure to be less likely. Therefore, they have less reason to keep sunk costs low, and optimal initial size increases. Compared to specific human capital, generic human capital is supposed to have a much smaller effect on entrepreneurial competence and self-confidence.

Second, human capital will impact the degree to which founders are affected by financial constraints. Generic human capital usually coincides with a higher personal wealth. Furthermore, both generic and specific human capital serves as a positive signal for external agents. The positive signal might be stronger in the case of specific human capital since the existence of directly applicable knowledge and skills should be particularly suited to convince agents of the founder's ability to succeed. Founders with higher human capital, particularly higher specific human capital, should thus be able to attract external funding more easily. Altogether, founders with a high level of human capital should be less exposed to financial constraints. However, entrepreneurial experience may only serve as a positive signal if the founder has been successful in his previous business. If he has failed, the signal to potential capital providers should be rather negative (Metzger, 2007). Moreover, his financial resources will be limited in this case because of financial obligations resulting from the previous business.

Finally, founders' human capital influences the firm's ability to attract good workers. Basically, employees might be reluctant to work in newly-established firms. Young firms face a high risk of firm closure (Geroski, 1995). Furthermore, wages (Brixy et al., 2007; Van Praag and Versloot, 2007) and employment stability (Schnabel et al., 2008) are lower in newly-established firms. Therefore, young firms might be faced with another type of resource constraints, namely labor supply restrictions. Since founders' human capital and survival prospects are related (Brüderl et al., 1992; Bates, 1990), the professional experience and the educational degree of the founders may serve job-searchers as a signal of good prospects of the firm. Labor supply should thus be less restricted if the founders have accumulated a high level of human capital. Subsuming the arguments, both the generic and specific components of founders' human capital should have a positive effect on a firm's start-up size. However, while both types of human capital will generally help to ease resource constraints and will increase the expected entrepreneurial earnings, the specific human capital in particular should increase a firm's efficiency, strengthen an entrepreneur's confidence in firm success, and serve as a positive signal to capital providers. Therefore, we expect the influence of the specific human capital to be greater than that of generic human capital. The second hypothesis is stated as follows:

Hypothesis 2: *Start-up size is positively influenced by the generic and specific human capital of the founders. The effect of specific human capital is higher than the effect of generic human capital.*

Finally, the size of new firms is expected to vary across industries. Since highly different technologies are employed in the production process and service delivery, scale economies do not only form established firms' size distribution but also influence new firms' start-up size. Given the entry decision, firms will start larger if they start their operations in industries with a high MES. Moreover, the effect of economies of scale is related to the size of the market or industry. Following Mata and Machado (1996), the larger the MES is relative to industry size, the greater is the probability that firm entry occurs at the expense of incumbents. Then, founders have an incentive to start relatively small in order to avert retaliation. Thus, for a given MES, start-up size will increase with industry size. The wage level in the industry is supposed to have an impact on start-up size, too. Wages in Germany are often determined by collective agreement on the industry level. Even if a start-up is not bound by a collective agreement, it might be forced to pay similarly high wages because otherwise it will be faced with severely restricted labor supply. In any case, the wage level in the industry influences the labor cost of the new firm and is likely to be negatively related to start-up size as measured by initial employment. Our third hypothesis is stated as follows:

Hypothesis 3a: *Start-up size is positively related to the extent of economies of scale in the industry and to industry size.*
Hypothesis 3b: *Start-up size is negatively related to the wage level in the industry.*

4.4 Empirical analysis

We quantify start-up size by the sum of the number of employees and founders at the time the firm is created. We decided to choose this measure instead of taking only the number of salaried employees because we want to capture the total number of working-places created in the firm. Given that most firms start without or only with a small number of employees, it is evident that founders carry out large part of the daily business in very young firms. It is only later that some of them start to hire more employees and increasingly focus on managerial tasks. Since we measure employment immediately after foundation, it seems appropriate to include the labor input of the founders into our measure of start-up size.[3]

Specifically, start-up size is measured both in full-time equivalents and in head counts. As argued above, the number of persons engaged might be a more meaningful measure for employment than the number of working hours agreed for very young firms with a highly volatile workload. Moreover, we are interested in explaining the effective number of working-places - be they full-time or part-time - created by the firms.

4.4.1 The econometric model

Accordingly, we estimate the determinants of a firm's start-up size using two different models. In the first model, we measure start-up size of firm i - y_i - as the full-time equivalent of the sum of the number of founders and the number of employees in logarithm. The linear model is expressed by:

$$ln(y_i) \quad = \quad \boldsymbol{x}_i^{'}\boldsymbol{\beta}_1 + \boldsymbol{z}_i^{'}\boldsymbol{\beta}_2 + \boldsymbol{f}_i^{'}\boldsymbol{\beta}_3 + \boldsymbol{w}_i^{'}\boldsymbol{\beta}_4 + u_i \qquad \forall i = 1, \ldots n,$$

where n is the number of firms in our estimation sample, $\boldsymbol{x}_i$ represents market entry strategies of the firms, $\boldsymbol{z}_i$ are the variables reflecting the human capital of the founders, $\boldsymbol{f}_i$ indicates public funding, and $\boldsymbol{w}_i$ is a set of industry-specific factors (see Table 4.1 for a variable description); $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$ and $\boldsymbol{\beta}_4$ are the vectors of parameters to be estimated. We compute ordinary least squares (OLS) estimates. Because start-up size is measured

[3] By this we follow the approach of Barkham (1994) who also added the number of founders to the number of employees in order to calculate the total employment in the firm. Likewise, Colombo et al. (2004) used the sum of the number of employees and founders as an alternative measure of start-up size next to the number of salaried employees.

on a logarithmic scale, the coefficients measure the semi-elasticities of y with respect to regressors measured in levels. For regressors in logarithms, the respective coefficients can be interpreted as elasticities.

In the second model, we look at employment measured in head counts and use a count-data model to estimate the parameters of interest. The Poisson regression model might be used to compute estimates. One assumption of the poisson model is that the variance of the dependent variable equals its mean. This assumption of the Poisson model is violated here. The variance of start-up size is larger than the mean ("overdispersion"). The most common alternative of the Poisson model is the negative binomial (NB) model, which relaxes the assumption of mean-variance-equality and generalizes the Poisson model by introducing an individual, unobserved effect into the conditional mean (Greene, 2003, pp 744ff). We choose the NB II model (Cameron and Trivedi, 1986) to shape the conditional variance of the dependent variables:[4]

$$\mathrm{Var}(y_i|\boldsymbol{x}_i, \boldsymbol{z}_i, \boldsymbol{f}_i, \boldsymbol{w}_i) = E(y_i|\boldsymbol{x}_i, \boldsymbol{z}_i, \boldsymbol{f}_i, \boldsymbol{w}_i)\left[1 + \alpha E(y_i|\boldsymbol{x}_i, \boldsymbol{z}_i, \boldsymbol{f}_i, \boldsymbol{w}_i)\right] \ \ \forall i = 1, \ldots, n,$$

where y_i represents the start-up size in head counts. The parameter α is an estimate of the degree of overdispersion: the larger α, the greater the amount of overdispersion in the data. When α is zero, negative binomial has the same distribution as Poisson. A test of the Poisson distribution is carried out by testing the hypothesis $\alpha = 0$ using a Wald test. The hypothesis is denied and the negative binomial model should be preferred to the Poisson model.

The conditional mean $E(y|\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{f}, \boldsymbol{w})$ is of the exponential form, i.e. $E(y|\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{f}, \boldsymbol{w}) = exp(\boldsymbol{x}'\boldsymbol{\beta}_1 + \boldsymbol{z}'\boldsymbol{\beta}_2 + \boldsymbol{f}'\boldsymbol{\beta}_3 + \boldsymbol{w}'\boldsymbol{\beta}_4)$. Differentiation yields $\frac{\partial E[y|\boldsymbol{x},\boldsymbol{z},\boldsymbol{f},\boldsymbol{w}]}{\partial x_j} = \beta_{1j} \cdot exp(\boldsymbol{x}'\boldsymbol{\beta}_1 + \boldsymbol{z}'\boldsymbol{\beta}_2 + \boldsymbol{f}'\boldsymbol{\beta}_3 + \boldsymbol{w}'\boldsymbol{\beta}_4)$. This expression measures the increase in the expectation of y due to a one-unit change in the jth regressor. The marginal effect varies across firms since it depends on $exp(\boldsymbol{x}_i'\boldsymbol{\beta}_1 + \boldsymbol{z}_i'\boldsymbol{\beta}_2 + \boldsymbol{f}_i'\boldsymbol{\beta}_3 + \boldsymbol{w}_i'\boldsymbol{\beta}_4)$. Therefore, as in the log-level ordinary least squares model for the full-time equivalents, the coefficients measure the relative change in the expected response variable induced by a unit change in the respective regressor, which is the semi-elasticity. If a regressor is measured in logarithms, the respective coefficient can be interpreted as elasticity (Cameron and Trivedi, 2005).

[4]We prefer the NB II model to the NB I model as the log-likelihood for NB II is larger than that for NB I in our model.

Measuring the effect of aggregate variables on micro units by merging aggregate industry data with micro observations, standard errors can be seriously biased downward. The failure to account for correlation of errors within the different industry groups (here: NACE 2-digits), which is a consequence of this bias, can result in spurious findings of statistical significance of the aggregate variables (Moulton, 1990). Therefore, we control for the within-group disturbance correlation by computing the correct covariance matrix of the estimator. This cluster-robust estimator of the variance-covariance matrix is both heteroskedasticity-robust and cluster-robust. To take into account that firms from high-tech industries are oversampled in the survey, we run weighted regressions using sample weights.

4.4.2 The data

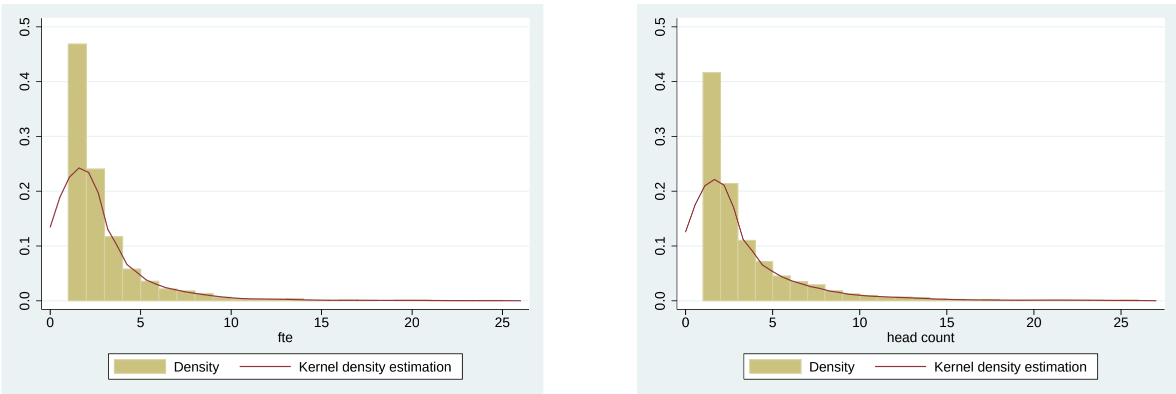
The data-set used for the empirical analysis consists of around 5,000 German firms which were established between 2005 and 2007. It is part of the "KfW/ZEW Start-Up Panel", a newly launched panel of German start-ups in various industries. The panel is a joint activity of the "KfW-Bankengruppe", a publicly-owned bank, the Centre for European Economic Research (ZEW) and Creditreform, Germany's biggest credit rating agency. The underlying population, from which a stratified[5] random sample was drawn, is composed of all start-ups recorded by Creditreform which are operating in manufacturing, construction, and services and which were founded in the years 2005 to 2007. In the following years, these firms shall be observed up to a firm age of seven years. In order to have enough observations for viable empirical analyses of high-tech industries, new high-tech start-ups were oversampled. The sample consists of high-tech start-ups and non-high-tech start-ups in equal share. A detailed list of all industries included in the KfW/ZEW Start-Up Panel can be found in Table 4.4 in the Appendix. The first survey wave, on which this analysis relies on, was conducted in 2008. Detailed information about the founders, their human capital, a firm's labor demand, and other firm characteristics were retrieved by means of computer-assisted telephone interviews. In order to be able to ascertain the effect of industry characteristics, we add industry data to each firm observation according to its industry classification code (NACE) and its year of foundation. Industry data was retrieved on the 2-digit level of the annual enterprise statistics of industry, trade, and services made publicly available by Eurostat. One of the industry variables (minimum efficient scale) was calculated using

[5]Stratification criteria were the year of establishment, the industry and KfW-funding.

the Mannheim Enterprise Panel (MUP), the most comprehensive existing firm-level data-base of nearly all German companies. The underlying data for the MUP are provided by Creditreform. These additional industry variables were merged with the firm-level data of the KfW/ZEW Start-Up Panel.

4.4.3 The variables

We define the initial size of the firm by the total number of employees and founders on the day of foundation. The group of employees contains full-time and part-time employees, who are included in the German social insurance system, and marginally employed persons, who do not earn more than 400 Euro per month and therefore are not included in the social insurance system. Family members, who take an active part within the new-born firm, freelancers, trainee students, subcontracted workers, and apprentices are counted among the employees, too. We calculate full-time equivalents as well as head counts.



(a) full-time equivalents (b) head counts

Figure 4.1: Histogram and kernel density estimate of start-up size in *full-time equivalents* and *head counts*

Source: KfW/ZEW Start-Up Panel 2008, authors' calculations.

On average, 3 persons worked in a newly established firm of our estimation sample on the day of foundation. For full-time equivalents (fte) we calculate an average of 2.5 fte. The median is 2 for full-time equivalents and head counts. For both measures a histogram was drawn and the kernel density was estimated (see Figure 4.1). The distribution of start-up size in full-time equivalents and the distribution of start-up size in head counts is both positively skewed. The distributions resemble each other.

Besides the description of the variables below, a summarizing definition and descriptive statistics of all variables used in the empirical analysis can be found in Table 4.1. As described in the development of the hypotheses, we expand the analysis of the determinants of start-up size in examining the role of entry strategies. On the one hand, we look at an entry strategy based on innovation. An innovation-based entry strategy relies on the development of new technologies or innovative products which allow firms to find a niche position in the market. We capture an innovation-based strategy with a dummy variable which indicates if a firm carries out research and development activities (*R&D*) continuously. In our sample, 16 percent of the firms are conducting R&D continuously (see Table 4.1).

Table 4.1: Description of variables

Variable	Description	Mean	Std.dev.
Dependent variables			
Log(start-up size)	Logarithm of total employment at firm foundation measured in full-time equivalents.	0.644	0.689
Start-up size (head count)	Total employment at firm foundation measured in head counts.	3.028	3.232
Independent variables			
Entry strategies			
Continuous R&D	Firm is conducting R&D continuously.	0.158	0.365
Independency entrepreneurship	Firm foundation was driven by the wish to work self-determined.	0.447	0.497
Necessity entrepreneurship	Firm foundation was driven by necessity (unemployment or no adequate dependent employment).	0.191	0.393
Opportunity entrepreneurship	Firm foundation was based on a precise business idea or market gap.	0.320	0.466
Spin-out entrepreneurship	Firm foundation was pushed by the former employer.	0.028	0.166
Generic human capital			
Graduate	Single founder is a university graduate / at least one graduate in the team of founders.	0.392	0.488
Log(age)	Logarithm of the (oldest) founders' age.	3.635	0.245

Continued on next page...

Variable	Description	Mean	Std.dev.
Specific human capital			
Entrepreneurial experience (not successful)	Single founder has entrepreneurial experience / at least one founder has entrepreneurial experience in the team of founders. The founder's previous business has become insolvent or has been liquidated.	0.127	0.333
Entrepreneurial experience (successful)	Single founder has entrepreneurial experience / at least one founder has entrepreneurial experience in the team of founders. The entrepreneur's previous business still exists.	0.214	0.410
Top manager	Single founder has been a top manager / at least one founder has been a top manager in the team of founders before firm foundation.	0.212	0.409
Log(industry experience)	Logarithm of the years of professional experience in the same industry.	2.265	1.724
Public funding			
Public funding (BA)	Firm has received initial funding from the federal employment agency.	0.376	0.484
Public funding (non BA)	Firm has received initial funding from other public agencies than the federal employment agency.	0.269	0.443
Industry variables			
Log(industry size)	Logarithm of the number of employees in the same industry (NACE 2-digits) in the year prior to firm foundation.	13.743	0.994
Log(labor costs)	Logarithm of the average labor cost per employee in the same industry (NACE 2-digits) in the year prior to firm foundation (in thousand Euros).	3.449	0.423
MES	Minimum efficient scale (median size of a firm in the same industry; NACE 2-digits).	2.018	1.447
High-tech	Firm belongs to the high-tech industries (NACE 4-digits).	0.424	0.494

Source: KfW/ZEW Start-Up Panel 2008, authors' calculations.

On the other hand, we consider the main motive of the founders to start the firm. We distinguish four types of motivations which can be associated with different start-up size decisions: independency entrepreneurship, necessity entrepreneurship, opportunity entrepreneurship, and spin-out entrepreneurship. We declare *independency entrepreneurship* to be the base category. Independency entrepreneurship represents founders who state that being self-employed was the main reason for founding the new firm which is true for one half of the firms in our sample. *Opportunity entrepreneurship* stands for firm foundations which were based on a precise business idea or an opened-up market gap. Almost one third of the firms in our sample stated to follow such an entry strategy. *Spin-out entrepreneurship* denotes firm foundations which are pushed by the founders' former employer. Spin-out entrepreneurship comprises 3 percent of our sample firms. *Necessity entrepreneurship* suggests that the firm foundation was mainly driven by avoiding unemployment or the absence of an adequate dependent employment. This last motive was the central reason to enter self-employment for one fifth of the firms in our sample.

A further key explanatory factor for start-up size in our models is the founders' human capital. We distinguish between generic and specific human capital (see Table 4.1). Generic human capital is measured by the education of the founders or the founding team, respectively: *Graduate* has value 1 if the single founder or at least one member in the team of founders has a university or college degree, otherwise it is zero. Due to this definition, nearly 40 percent of firms in our sample are graduate foundations (see Table 4.1).

The age of the founders - or oldest founder's age in case of a team foundation - measured in logarithm *(Log(age))* approximates the general professional experience and is a second factor of generic human capital. These variables reflect general knowledge of the founders which cannot be directly applied to the entrepreneurial tasks in the newly established enterprise. They are also supposed to be proxies of personal wealth.

We measure specific human capital by factors indicating experience which can be directly utilized in business operations. One of these factors is the specific professional experience of the founder(s) measured in logarithms of the number of years of professional experience in the industry the new-born firm is operating in *(Log(experience in industry))*.[6]

In addition, we operationalize managerial experience using three dummy variables. The first variable indicates that at least one founder has been employed as a top manager in another firm before foundation (*top manager*) and hence has gathered experience as a firm's executive. The other two dummy variables indicate that at least one of the founders has been an entrepreneur before foundation. We differentiate between successful and not successful entrepreneurship experience. *Successful entrepreneurial*

[6]In case of a team foundation, we observe the years of experience of the founder who has worked the largest time in the relevant industry.

experience denotes that the previous business still exists. Either it is still managed by the founder or it has been transferred or sold to someone else. In contrast, *not successful entrepreneurial experience* is assigned to founders who were entrepreneurs prior to firm foundation, but the previous business has become bankrupted or has been liquidated. We expect a distinctive positive effect of successful entrepreneurial experience on start-up size. In comparison, firms of former entrepreneurs who fail with their businesses are expected to start not larger or, indeed, at a smaller scale than the average foundation. Unsuccessful restarters might have access to fewer resources due to the failure of their prior businesses, and they might be less confident about market and earnings prospects.

We control for public financial support the firms received since we expect that it will influence start-up size via relaxing the financial constraints firms face. More than one half of the new-born firms in our sample got external finance from public agencies. In our models, we differentiate between two different sources of public funding: programs oriented by industrial policy and labor market programs. In Germany unemployed persons can apply for funding from the German Federal Employment Agency (Bundesagentur für Arbeit - BA) to start-up their own business. The volume of financial support from the BA is just intended to ease the step into self-employment and to ensure the founder's living in the first months. This type of funding *(Public funding (BA))* is comparatively low[7] and is not expected to have a noticeable effect on start-up size. By contrast, financial support from other public agencies *(Public funding (non BA))*, e.g. the KfW-Mittelstandsbank or regional authorities, stems from governmental spending programs which are intended to foster the competitiveness and growth in the economy by supporting start-ups. Funding of this kind may reach a large amount of money and thus should enable founders to take up substantial investments.

The industry variables are selected to capture some important industry characteristics which are assumed to affect start-up size as stated in hypotheses 3a and 3b: industry size, level of labor cost, and the extent of economies of scale in the industry. *Log(industry size)* is the logarithm of the number of employees and *Log(labor costs)* is the logarithm of the average labor cost per employee in the industry to which a start-up belongs in the year prior to firm foundation. These two variables originate in statistics from Eurostat (see above). The minimum efficient scale (*MES*) is measured

[7] The BA provides for the first nine months after founding a business beneficiaries of the foundation grant ("Gründungszuschuss") to previously unemployed founders. They receive a grant at their personal level of unemployment insurance benefits, plus 300 Euro per month to help meet social security costs.

by the median size of a firm in the same industry. The MES is computed using the firm micro-data of the Mannheim Enterprise Panel (MUP). Firms belonging to *high-tech* industries - which are 42 percent of our estimation sample - are marked by a dummy to control for special features of these firms which cannot be covered by the other industry variables used here. [8]

4.4.4 Estimation results

First, we look at the results of the OLS regression using start-up size measured in full-time equivalents as a dependent variable (see Table 4.2). We find that firms conducting R&D continuously start larger than others. This supports hypothesis 1a, which states that an entry strategy based on the objective to serve the market with innovative products tends to have a positive effect on initial size. On average, the number of full-time equivalent employees is about 11 percent higher if the firm conducts R&D continuously. The primary motivation of the founders affects start-up size, too. Opportunity entrepreneurs and spin-out entrepreneurs tend to choose a larger initial size than founders that are first of all motivated by independency, which is the reference group. We find that the positive effect on start-up size is larger for spin-out entrepreneurs than for opportunity entrepreneurs. While spin-out entrepreneurs start their firm with 35 percent more full-time equivalent employees than independency entrepreneurs, opportunity entrepreneurs' start-up size is (only) about 15 percent higher than that of independency entrepreneurs. If the foundation was primarily driven by necessity, this has an insignificant negative effect on start-up size. Thus, hypothesis 1b is confirmed insofar as opportunity and spin-out entrepreneurs indeed tend to start larger firms than independency and necessity entrepreneurs.

However, we do not find evidence for our assumption that necessity entrepreneurs choose a smaller start-up size than independency entrepreneurs if start-up size is measured in full-time equivalents.

[8] The use of one high-tech industry dummy is sufficient since our industry variables have shown to capture industry effects sufficiently. We estimated all regressions including a set of industry dummies, but all dummies have shown to be not significantly different from zero. However, it is necessary to distinguish high-tech industries from other industries since industry variables are merged to firm level data on the NACE 2-digit level, but high-tech industries are defined on the NACE 4-digit level.

Table 4.2: Determinants of start-up size: results of the OLS and NB models

	OLS log(fte)		NB II head count	
	coeff.	se	coeff.	se
Entry strategies				
Continuous R&D	0.105**	(0.049)	0.113	(0.069)
Necessity entrepreneurship[(1)]	-0.073	(0.045)	-0.153**	(0.065)
Opportunity entrepreneurship[(1)]	0.154***	(0.037)	0.089*	(0.051)
Spin-out entrepreneurship[(1)]	0.350***	(0.087)	0.586***	(0.143)
Generic human capital				
Graduate	0.133***	(0.040)	0.135**	(0.062)
Log (age)	0.170**	(0.076)	0.245**	(0.110)
Specific Human Capital				
Entrepr. exp. (not sucessf.)[(2)]	0.035	(0.064)	0.114	(0.092)
Entrepr. exp. (sucessf.)[(2)]	0.248***	(0.055)	0.308***	(0.072)
Top Manager	0.191***	(0.071)	0.249***	(0.093)
Log (experience in industry)	0.005	(0.010)	0.004	(0.015)
Funding				
Public funding (BA)	-0.040	(0.039)	-0.088*	(0.052)
Public funding (non BA)	0.158***	(0.040)	0.237***	(0.067)
Industry variables				
High-tech	0.101	(0.068)	0.178*	(0.102)
Log (industry size)	-0.068**	(0.029)	-0.078**	(0.039)
Log (labor costs)	-0.357***	(0.108)	-0.553***	(0.132)
MES (median)	0.081***	(0.017)	0.108***	(0.023)
Constant	1.688**	(0.709)	2.504***	(0.934)
α			0.284***	(0.021)
Observations	4748		4748	
R-squared / χ^2	0.179		605.3	
Log-likelihood			-1,077,776	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses. Weighted estimations. References: (1) Independency entrepreneurship, (2) No entrepreneurial experience.

Source: KfW/ZEW Start-Up Panel 2008, Eurostat and MUP, authors' calculations.

Results further indicate a significant effect of both generic and specific human capital components on initial employment. As to the generic human capital components, results reveal that founders who are university or college graduates start larger firms than less educated founders. Firms with graduated founders start on average with 13 percent more full-time equivalents.

Moreover, start-up size increases with the founder's age which is supposed to mirror a founder's general work experience. The elasticity of start-up size with respect to founder's age is about 0.17, i.e. if the founder's age increases by 1 percent, start-up size - as measured in full-time equivalents - increases by 0.17 percent. Although the elasticity is small, it is still significantly different from zero. Both the graduate and the age coefficient might also reflect a wealth effect since the personal wealth usually increases with the level of education and with age. Wealth relaxes possible financial constraints forcing founders to start their firm below their optimal initial size.

As to the specific human capital components, we find that having been successful as an entrepreneur previously (i.e. the prior business still exists) increases the start-up size of the new venture. Compared to firms the founders of which have no entrepreneurial experience, firms start at a scale which is 25 percent larger if at least one founder has been successful as an entrepreneur previously. By contrast, having been unsuccessful as an entrepreneur prior to firm foundation (i.e. the prior business has become insolvent or has been liquidated) does not have any significant influence on initial size. This indicates that entrepreneurial experience only leads to a higher start-up size if the previous entrepreneurial activity has been successful. Another result is that founders who have gathered managerial experience tend to start larger firms than other founders. Start-up size of those firms is 19 percent larger on average. Altogether, it seems that having (successfully) led a company previously, be it as self-employed or employed worker, gives founders trust in their own entrepreneurial abilities and the future performance of the new firm. Thereby, it induces them to choose a larger start-up size. Finally, professional experience in the same industry does not have a significant influence on start-up size. In consideration of the significant effect of founders' age on start-up size, this would imply that it is rather general work experience than industry-specific experience which makes founders feel confident about their venture and choose a larger initial size. Nevertheless, the comparison of the coefficients of the generic and specific human capital components altogether, shows that specific human capital has a larger impact on initial size than generic human capital. This confirms hypothesis 2 and previous results of Colombo et al. (2004).

We further observe that funding from the federal employment agency has no significant effect on initial size. By contrast, we find that funding from other public agencies does increase the start-up size. This type of funding increases start-up size in full-time equivalents by 16 percent. These results are in line with our conjecture that the amount of funding provided by the BA is too small to affect the level of initial investment. However, public funding provided by other agencies relaxes financial constraints and enables founders to start larger firms. However, one should be somewhat cautious with this interpretation because of the endogenous character of the funding variable. The scale of the start-up project may influence the probability of both applying for public funding and receiving public funding.

As to the industry variables, our results only partly confirm hypothesis 3a. As expected, the extent of economies of scale is positively related to start-up size. If the MES increases by 1 unit, start-up size increases by 8 percent. But as it was already the case in previous studies, we do not find evidence of a positive relationship between start-up size and industry size. In fact, start-up size tends to decrease with industry size according to our results. However, the effect is rather small in size. The elasticity of the number of full-time equivalent employees with respect to industry size is only -0.068. We further find that the average labor cost is negatively related to start-up size, which confirms hypothesis 3b. If labor costs increase by 1 percent, start-up size in full-time equivalents decreases by 0.357 percent. This result is reasonable since price elasticities of labor demand are usually found to be small in Germany (see Falk and Koebel, 2001; Addison et al., 2008). The fact of operating in the high-tech industries does not significantly affect start-up size.

The results of the negative binomial model using head counts as dependent variable by and large confirm the results of the OLS regression. Since the coefficients estimated in the negative binomial model can be interpreted as semi-elasticities for regressors in levels and elasticities for regressors in logarithms (see section 4.4.1), the coefficients of the negative binomial model can be directly compared to the OLS estimates. There are no differences regarding the sign of the parameter estimates between the two models and only a few variations concerning their significance. For example, the positive effect of continuous R&D on initial size is no longer significant in the negative binomial model.

Accordingly, hypothesis 1a, which states that an innovation-based entry strategy leads to a larger start-up size, is not confirmed when initial employment is measured in head counts. Thus, firms performing R&D continuously have a higher initial employment when measured in full-time equivalents, but not when measured in head counts. This suggests that R&D tasks are primarily carried out by full-time employees and to a lesser extent by employees working part-time for the firm, marginally employed persons, freelancers, trainee students and apprentices.

Another difference is that necessity entrepreneurship exerts a significant negative effect in the negative binomial model so that hypothesis 1b is now fully confirmed. Start-up size as measured in head counts is approximately 15 percent lower for necessity entrepreneurs. Necessity entrepreneurs tend to employ a smaller number of persons at start-up than the reference group of independency entrepreneurs, whereas the initial employment volume - as measured in full-time equivalents - does not differ significantly. Thus, necessity entrepreneurs do not generally start smaller firms but - given a certain employment volume - aim to keep the number of employees low. A similar result is obtained for founders who receive funding by the BA and who - just as necessity entrepreneurs - are often motivated by the aim to escape from unemployment. The negative effect of being funded by the BA is (weakly) significant only in the negative binomial model and not in the OLS model. The negative binomial model reveals that new firms which have received funding from the BA start at a scale which is around 9 percent lower than for new firms which have not received public funding.

Additionally, some interesting implications can be drawn when looking at the size of the effect and compare it to the effect obtained from the OLS for the full time equivalents. The effect of spin-out entrepreneurship on start-up size is much larger if start-up size is measured in head counts. Start-up size in head counts is around 59 percent higher for spin-out entrepreneurs than for independency entrepreneurs. Remember, the effect amounts to 35 percent if start-up size is measured in full-time equivalents. The results of both models imply that spin-out entrepreneurs start at a larger scale, but it seems that they start with more part-time workers since the effect is higher for head counts than for full-time equivalents. Similarly, the (negative) elasticity with respect to labor costs is larger for start-up size measured in head counts than for start-up size measured in full-time equivalents. Thus, if labor costs rise, entrepreneurs are reluctant to start their venture with hiring a large amount of persons while the amount of full-time equivalents cannot be lowered too much. For most of the explaining variables the coefficients -

and accordingly the relative effect - are at least sightly larger in absolute terms when start-up size is measured in head-counts. This accompanies the results of Gottschalk et al. (2008) who find that new firms heavily rely on flexible work arrangements, such as part-time work and marginal employment.

Interestingly, the effect of the variable which indicates that one of the founders is a university or college graduate is approximately the same regardless of the measure of start-up size. Graduates start their firms 13.3 percent (13.5 percent for head counts) larger than other founders. This makes us suppose that graduates not only start larger firms but also prefer to employ full-time workers instead of part-time workers or marginally employed persons.

Differences between the effects of the two models might not only result from the different measures regarding start-up size but also from the econometric model used to estimate the effects. As a robustness check and in order to assess how much of the difference between model 1 and model 2 is due to changing the econometric model, head counts are logarithmically transformed and effects are estimated using OLS. The results of this regression are presented in Table 4.3 in the Appendix. It can be seen that most of the differences between model 1 and model 2 is due to the measure of start-up size. Coefficients of the OLS regression presented in Table 4.3 lie in between the coefficients of model 1 (fte) and model 2 (head counts), but they are mostly very close to those of the negative binomial regression.

All in all, the results reveal that it does not make a big difference for explaining initial firm size whether employment is measured in full-time equivalents or in head counts. This confirms our supposition that due to the highly variable work load in very young firms the working hours agreed in labor contracts are not necessarily a more meaningful indicator of employment than the number of persons employed.

4.5 Conclusions

In this chapter, we examined how entry strategies, specific and generic human capital of a new-born firm's founders and industry characteristics affect the choice of initial size. Since it is well known that initial size has a positive impact on early firm survival, getting a more detailed picture of the determinants of initial firm size is desirable. As most of the rare literature on initial firm size focuses on industry characteristics, we contribute to the understanding of the determinants of initial firm size by drawing attention to firm-specific factors such as founders' entry strategies and founders' human capital composition. We applied two different models. The first explains the determinants of start-up size measured in full-time equivalents, the second using head counts.

First insights have been gained on how a chosen entry strategy influences start-up size. Entry strategies crucially determine initial size. The two models reveal that firm formations driven by opportunity as well as spin-out entrepreneurship start at a larger scale. The leading decision to be active in research and development has a positive impact on the start-up size in full-time equivalents, but does not affect start-up size in head counts.

Concerning generic human capital, we find that having a university degree has a positive influence on total employment for both full-time equivalents and head counts. The same applies for general working experience proxied by the founder's age. With regard to the specific human capital components, we find that successful entrepreneurial experience and managerial experience gained in dependent employment support a higher start-up size. Altogether, specific human capital tends to have a larger impact on initial size than generic human capital.

In order to provide comparable results we controlled for various industry variables. Our results are by and large in line with the existing literature. Industry size and average labor costs in the industry are found to have a negative effect on start-up size while operations start at a larger scale if the minimum efficient scale which is observed in the respective industry is higher.

Our results show that - for a better understanding of the size distribution of newly established firms - it is useful to account for founder-specific, firm-specific, and industry specific factors.

4.A Appendix

4.A1 Robustness check

Table 4.3: Determinants of start-up size: results of the OLS for log(head count)

	OLS log(head count)	
	coeff.	se
Entry strategies		
Continuous R&D	0.116*	(0.059)
Necessity entrepreneurship$^{(1)}$	-0.091*	(0.052)
Opportunity entrepreneursh.$^{(1)}$	0.149***	(0.042)
Spin-out entrepreneurship$^{(1)}$	0.438***	(0.117)
Generic human capital		
Graduate	0.134***	(0.047)
Log (age)	0.217**	(0.086)
Specific Human Capital		
Entrepr. exp. (not sucessf.)$^{(2)}$	0.042	(0.073)
Entrepr. exp. (sucessf.)$^{(2)}$	0.301***	(0.061)
Top Manager	0.213***	(0.076)
Log (experience in industry)	0.001	(0.013)
Funding		
Public funding (BA)	-0.046	(0.043)
Public funding (non BA)	0.203***	(0.052)
Industry variables		
High-tech	0.163*	(0.085)
Log (industry size)	-0.072**	(0.033)
Log (labor costs)	-0.473***	(0.129)
MES (median)	0.087***	(0.020)
Constant	2.029**	(0.845)
Observations	4748	
R-squared	0.181	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses. Weighted estimations. References: (1) Independency entrepreneurship, (2) No entrepreneurial experience.

Source: KfW/ZEW Start-Up Panel 2008, Eurostat and MUP, authors' calculations.

4.A2 Industry classification

Table 4.4: Industries included in the KfW/ZEW Start-Up Panel

	Industry	NACE Rev. 1.1 (WZ 2003)
	High-tech industries	
1	High-technology manufacturing	23.30, 24.20, 24.41, 24.42, 29.60, 30.02, 32.10, 32.20, 32.30, 33.10, 33.20, 33.30, 35.30, 24.13-4, 24.16-7, 24.51, 24.61, 24.63-4, 24.66, 25.11, 25.13, 26.15, 29.11-4, 29.24, 29.31-2, 29.41-3, 29.52-6, 30.01, 31.10, 31.20, 31.40, 31.50, 31.61-2, 33.40, 34.10, 34.30, 35.20
2	Technology-intensive services	64.3, 72 (w/o 72.2), 73.1, 74.2, 74.3
3	Software	72.2
	Non-high-tech industries	
4	Knowledge-intensive services	73.2, 74.11-4, 74.4
5	Low-technology manufacturing	15-37 (w/o industries classified in 1)
6	Other business-related services	60.3, 61, 62, 63.1-2, 63.4, 64.1, 71.1-3, 74.5-8 (w/o 74.87.7), 90
7	Consumer-related services	55, 60.1-2, 63.3, 65, 66, 67, 70, 71.4, 80.4, 92, 93
8	Construction	45
9	Wholesale and retail trade (without trade agents)	50-52(w/o 51.1)

Notes: High-technology manufacturing: manufacturing industries with average (OECD average) R&D expenditure > 2% of total sales.

Source: Legler and Frietsch (2006), Classification of KfW/ZEW Start-Up Panel 2008 (see Fryges et al., 2010).

5 Heterogeneous labor demand of newly established firms

5.1 Introduction

Addressing the role of start-ups for the creation of sustainable employment is one of the major aims in entrepreneurship research. Based on the results of Birch (1981), who found that young firms were largely responsible for job creation in the U.S. during the 70s, aggregate employment effects are in the interest of most studies. While measuring gross employment creation (number of jobs created by start-ups each year) is relatively easy and done for most developed countries periodically, detailed macroeconomic analyses are challenging because they have to account for the fact that more than half of the start-ups do not survive the first 8-10 years (Boeri and Cramer, 1992) and for crowding out of jobs in matured firms.

Microeconometric analysis disentangles the determinants of firms' start-up size and young firms' employment growth. Several factors have been shown to be related to a firm's start-up size and employment growth in the first years of its existence. These are firm-specific factors, such as the legal form of a firm, funding, innovation activities, and industry characteristics, such as economies of scale. Moreover, the generic and specific human capital of new firms' founders have been shown to be positively related to a firm's early labor demand. As a main novelty, this study is not interested in the quantity, but the quality of jobs created in young entrepreneurial firms. Therefore, the structure of jobs in young firms is investigated. The study aims to identify the determinants of labor demand for different levels of employees' education. Since studies on the firm level have shown that the human capital of the founders is an important predictor for young firms' labor demand when labor is treated as homogeneous, this study focuses on the importance of entrepreneurs' human capital on heterogeneous labor demand.

Heterogeneous labor demand has been investigated first and foremost for matured firms. In this context, estimating own-wage and cross-wage elasticities and testing the hypothesis of a skill-biased technological change have been the major issues. Investigating the impact of entrepreneurs' human capital on heterogeneous labor demand of newly established firms will thus contribute not only to the understanding of young firms' part in creating sustainable employment but also to the literature of heterogenous labor demand of firms in general.

There are several reasons why entrepreneurs' human capital shall be related to the qualification structure of young firms' employees. Founders' human capital will largely determine the business idea and the type of products and services a firm offers. Typically, highly educated founders will sell more sophisticated products and services. As a consequence, production and sale of this kind of products require also a higher educational level of the firm's employees.

Moreover, a higher level of founders' human capital relaxes financial constraints of a new-born firm. Founders with a high level of human capital usually have higher private wealth, and they often receive external financing more easily. Funding is especially important if a firm plans to hire high-skilled personnel because hiring high-skilled workers will be relatively more expensive than hiring medium-skilled or low-skilled workers. Severe financial constraints might therefore hinder young firms to employ high-skilled workers while it might still be possible to hire workers with a lower skill level. Additionally, low-skilled workers might be less reluctant to accept less favorable labor agreements, such as fixed-term work contracts or marginal employment.

Furthermore, young firms may face substantial restrictions on the supply of high-qualified labor. Usually, high-skilled workers have good labor market opportunities. Competing with established firms for high-qualified labor, young firms might lose since workers often prefer to work in well-established firms, which are typically larger and pay higher wages (Brixy et al., 2007; Van Praag and Versloot, 2007). Furthermore, employment stability is expected to be higher in well-established firms (Schnabel et al., 2008). On the other hand, workers may accept lower salaries if they expect non-financial working conditions, e.g. via flat hierarchies, to be better in young companies. Supply-side restrictions for young firms may be less severe the higher the human capital of the founders. The professional experience and the educational degree of the founders may serve as a signal for good prospects of the firm. Evidently, founders' human capital and survival prospects are related (Brüderl et al., 1992; Bates, 1990).

In order to investigate the importance of founders' human capital for heterogeneous labor demand of young firms empirically, I apply different kinds of corner solution outcome models. Comparing Tobit models to various kinds of hurdle models, hurdle models turn out to fit the data best.

The analysis in this chapter covers a wide range of industries. Both manufacturing and services are included. Industries can be distinguished by their technology orientation and knowledge intensity. One can assume that especially in knowledge- and research-intensive industries, such as high-tech manufacturing or knowledge-intensive services, even young firms ask for more skills.

Entrepreneurs' human capital is found to be a major determinant of the qualification structure of the workforce in young firms. Furthermore, the estimation results are in line with the hypothesis of a skill-biased technical change and the hypothesis of capital-skill complementarity.

The remainder of the chapter proceeds as follows. Section 5.2 reviews the literature on heterogeneous labor demand in established firms. After that, I explain the theoretical framework for investigating heterogeneous labor demand. The methods, the data and the results of the empirical analysis are described in Section 5.4. Finally, I conclude.

5.2 Literature review

Until now, heterogeneous labor demand has been investigated almost exclusively for matured firms above a certain minimum size, often only for firms above 5 or 10 employees. When studying employment in newly founded firms, entrepreneurship research has mainly investigated aggregate employment effects (Acs and Müller, 2008; Fritsch and Weyh, 2006; Boeri and Cramer, 1992) or, at the firm level, employment growth (Calvo, 2006; Davidsson et al., 2002; Almus and Nerlinger, 1999), remuneration levels (Brixy et al., 2007; Brown and Medoff, 2003) and fringe benefits (Bernstein, 2002), employment turnover and stability (Schnabel et al., 2008; Brixy et al., 2005; Burgess et al., 2000; Lane et al., 1996a,b), codetermination (Addison et al., 2003), or start-up size (Gottschalk et al., 2009; Colombo et al., 2004; Mata and Machado, 1996). Studies analyzing the structure of the workforce in newly established firms are rare and solely descriptive (Gottschalk et al., 2008; Weißhuhn and Wichmann, 2000).

Though studies for young firms are missing, there exists a bulk of literature which deals with heterogeneous labor demand of mature firms. These studies are mainly motivated by shifts in the skill structure in developed economies over the last three decades and rising unemployment among the less skilled workforce. Empirical studies mainly test one or more of the three most prominent explanations for the rise of the share of high-skilled employees in an economy: 1) a skill-biased technical change, 2) increasing internationalization, 3) organizational change within a firm. [1] The hypothesis of a skill-biased technological change, i.e. technological progress will lead to larger share of high-qualified workers, is tested within a heterogeneous labor demand framework using different indicators and units of observation. Most common indicators are input and output indicators of innovative activities. These are R&D expenditures (Adams, 1999) and product or process innovations (Hujer et al., 2002). Furthermore, specific ICT indicators, such as the intensities of computer or internet usage (Maurin and Thesmar, 2004; Autor et al., 2003; Falk, 2001; Autor et al., 1998), or measures of innovative capital or investments (Doms et al., 1997) are used in order to assess the hypothesis of a skill-biased technological change. Studies investigating the hypothesis of a skill-biased technological change are either conducted with longitudinal industry-level data (Berman et al., 1998; Falk and Koebel, 2004; O'Mahony et al., 2008) or cross-sectional and longitudinal firm-level data (Kaiser, 2001; Aguirregabiria and Alonso-Borrego, 2001). The hypothesis of a skill-biased technological change is investigated and confirmed for most developed economies regardless of the indicator used. Jacobebbinghaus and Zwick (2002) show that technological change does not only reduce the relative demand for low-skilled workers but also reduces the demand for medium-skilled workers. A very informative literature review on the effect of technology on skill structure is provided by Chennells and van Reenen (2002) and Autor and Katz (1999).

Because Greenan and Guellec (1998) descriptively show that organizational change in terms of workers' autonomy and increased communication between workers is positively related to skill upgrading, more recent studies do not only focus on the technological change but also on the organizational changes within the firm. These studies find evidence that organizational change has a positive impact on skill upgrading within a firm (Piva and Vivarelli, 2004; Caroli and van Reenen, 2001; Falk, 2002), especially when combined with a high level of ICT (Bresnahan et al., 2002).

[1] A study of Piva and Vivarelli (2004) contains an excellent summary of the empirical literature on these topics both on the industry level and on the firm level.

Most studies dealing with globalization and the structure of the workforce are conducted on the sectoral level. Evidence is less clear since results differ depending on the indicator used to measure internationalization. Feenstra and Hanson (1996) measure international outsourcing by the share of intermediate goods imported out of total goods imported and find a positive influence on the demand for skilled workers. However, Slaughter (2000), who measures internalization by foreign affiliate employment, finds no effect of foreign direct investment on increased or decreased demand for skilled workers in parent companies. On the contrary, some of the results of a study by Silva (2008) are not consistent with the traditional trade theory in a Heckscher-Ohlin framework, i.e. international trade should lead to an increase in the relative demand for skilled workers in developed countries. Similarly, Elia et al. (2009) find that foreign activities also have, on the one hand, a negative impact on the demand for low-skilled workers, but, on the other hand, foreign activities have a negative impact on the demand for high-skilled workers if they take place in high income countries. Evidence on the firm-level is more in favor of the traditional trade theory. Head and Ries (2002) find evidence for a positive relationship between foreign direct investments and skilled employment if offshoring takes place in low-income countries. Also, Bandick and Hansson (2009) find a positive relationship between increased foreign presence within the same industry on skill upgrading in Sweden. Furthermore, if a firm becomes foreign-owned, relative demand for skilled labor increases if the firm was non-multinational before, but decreases if the firm was a Swedish multinational entity before the foreign acquisition has taken place.

5.3 Modeling heterogeneous labor demand

Factor demand for labor of different skill levels can be derived with the help of the duality of a firm's profit maximization problem. Taking the level of desired output (Y) as given, a firm's optimization behavior finds its expression by minimizing the costs. Because of its flexibility, a convenient choice for the cost function in the literature (Chennells and van Reenen, 2002; Caroli and van Reenen, 2001; Betts, 1997) is the translog cost function of Christensen et al. (1973). This function is a second-order approximation to an arbitrary functional form of the cost function. Analyzing heterogeneous labor demand of newly established firms, I consider a short-run cost function (see Brown and Christensen, 1981) with high-skilled labor L_H, medium-skilled labor

L_M and low-skilled labor L_L being variable factors of production. The stock of physical capital K^P and the stock of knowledge capital G, which captures technological change, are treated as quasi-fixed factors of production which do not have to be at their long-run optimal values. I extend the framework of analyzing heterogeneous labor demand as proposed by Bond and Van Reenen (2007) by using the generic and specific human capital of the firm's founders (K^H) as an additional quasi-fixed factor of production. Since founders' human capital largely determines the business idea and the type of products and services a firm offers and relaxes financial constraints and supply side restrictions, human capital is expected to have a positive influence on the skill structure within firms.

The augmented quasi-fixed translog cost function is given by

$$\begin{aligned}
ln(C) &= a_0 + \sum_i a_i ln(w_i) + \frac{1}{2}\sum_i \sum_j a_{ij} ln(w_i) ln(w_j) \\
&+ a_{K_1Y} ln(K^P) ln(Y) + a_{K_2Y} ln(K^H) ln(Y) + a_{GY} ln(G) ln(Y) \\
&+ a_{K_1K_2} ln(K^P) ln(K^H) + a_{GK_1} ln(G) ln(K^P) + a_{GK_2} ln(G) ln(K^H) \\
&+ a_Y ln(Y) \quad + \frac{1}{2} a_{YY} \left(ln(Y)\right)^2 \quad + \sum_i a_{iY} ln(w_i) ln(Y) \\
&+ a_{K_1} ln(K^P) + \frac{1}{2} a_{K_1K_1} \left(ln(K^P)\right)^2 + \sum_i a_{iK_1} ln(w_i) ln(K^P) \\
&+ a_{K_2} ln(K^H) + \frac{1}{2} a_{K_2K_2} \left(ln(K^H)\right)^2 + \sum_i a_{iK_2} ln(w_i) ln(K^H) \\
&+ a_G ln(G) \quad + \frac{1}{2} a_{GG} \left(ln(G)\right)^2 \quad + \sum_i a_{iG} ln(w_i) ln(G)
\end{aligned}$$

with $a_{ij} = a_{ji}$ for all i, j and $i, j = H, M, L$. Prices for variable inputs (skill differentiated wage levels) are denoted by w_i. Applying Shephard's (1953) Lemma, i.e. differentiating the quasi-fixed translog cost function with respect to the logarithm of the ith input price ($\frac{\partial ln(C)}{\partial ln(w_i)} = \frac{w_i}{C}\frac{\partial C}{\partial w_i} = \frac{w_i L_i}{C} = S_i$), yields the factor share equations:

$$\begin{aligned}
S_H &= a_H + a_{HH} ln(w_H) + a_{HM} ln(w_M) + a_{HL} ln(w_L) + a_{HY} ln(Y) \\
&\quad + a_{HK_1} ln(K^P) + a_{HK_2} ln(K^H) + a_{HG} ln(G) \\
S_M &= a_M + a_{MH} ln(w_H) + a_{MM} ln(w_M) + a_{ML} ln(w_L) + a_{MY} ln(Y) \\
&\quad + a_{MK_1} ln(K^P) + a_{MK_2} ln(K^H) + a_{MG} ln(G) \\
S_L &= a_L + a_{LH} ln(w_H) + a_{LM} ln(w_M) + a_{LL} ln(w_L) + a_{LY} ln(Y)
\end{aligned}$$

$$+a_{LK_1}ln(K^P) + a_{LK_2}ln(K^H) + a_{LG}ln(G)$$

By the the cost function property of linear homogeneity in input prices for each fixed level of output and quasi-fixed production factors (see Diewert, 2008), some restrictions can be placed on the parameters. Homogeneity implies that $\sum_i a_{ij} = 0$ for all j variable factors, $\sum_i a_{iY} = 0$, $\sum_i a_{iK_1} = 0$, $\sum_i a_{iK_2} = 0$, $\sum_i a_{iG} = 0$ and $\sum_i a_i = 1$. Furthermore, symmetry ($a_{ij} = a_{ji}$) is assumed. Because shares sum up to unity one equation is redundant and the system of equations can be simplified to

$$\begin{aligned} S_H &= a_H + a_{HH}ln(\frac{w_H}{w_M}) + a_{HL}ln(\frac{w_L}{w_M}) + a_{HY}ln(Y) \\ &\quad +a_{HK_1}ln(K^P) + a_{HK_2}ln(K^H) + a_{HG}ln(G) \qquad (5.1) \\ S_L &= a_L + a_{LH}ln(\frac{w_H}{w_M}) + a_{LL}ln(\frac{w_L}{w_M}) + a_{LY}ln(Y) \\ &\quad +a_{LK_1}ln(K^P) + a_{LK_2}ln(K^H) + a_{LG}ln(G). \qquad (5.2) \end{aligned}$$

Both the unknown parameters of equation (5.1) and equation (5.2) can be econometrically estimated by appending errors to the equations. The coefficient on the physical capital variable is expected to be positive in equation 5.1 or to be negative in equation 5.2 in order to be consistent with capital-skill complementarity. Likewise, both the coefficient on the human capital variable and the coefficient on the stock of knowledge capital are expected to be positive for high-skilled employees or negative for low-skilled employees.

5.4 Empirical analysis

5.4.1 The econometric models

5.4.1.1 Models of corner solution outcomes - Tobit and alternatives

Like many applications investigating demand, we are faced with corner solution outcomes when analyzing heterogeneous labor demand. This gives rise to excess zero observations in the data and a positive probability mass at zero. Applying ordinary least squares including zero observations would result in biased outcomes (Amemiya, 1984). The econometric literature has proposed several econometric models using latent variables in order to deal with censored or corner solution outcomes. The standard Tobit model, originally introduced by Tobin (1958), is used most commonly. This type of model is also called Type 1 Tobit according to Amemiya's (1984) classification of censored regression models. It is given by:

$$\begin{aligned} y_i^* &= \boldsymbol{x}_i^{'}\boldsymbol{\beta} + u_i, \qquad i = 1, 2, \ldots, n, \\ y_i &= \begin{cases} y_i^* & \text{if} \quad y_i^* > 0, \\ 0 & \text{if} \quad y_i^* \leq 0, \end{cases} \end{aligned}$$

with $u_i \sim \mathcal{N}(0, \sigma^2)$. The latent, unobserved dependent variable is denoted by y_i^*, while y_i and $\boldsymbol{x}_i$ are observed. Maximum likelihood estimation of the standard Tobit model maximizes the following log-likelihood function

$$\text{Log}L = \sum_0 ln \left[1 - \Phi\left(\frac{\boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma}\right)\right] + \sum_+ ln \left[\frac{1}{\sigma}\phi\left(\frac{y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma}\right)\right],$$

where $\Phi()$ denotes the cumulative density function of the standard normal distribution and $\phi()$ denotes the standard normal density function. Although widely used in empirical analyses, the standard Tobit model might be too restrictive since it strongly relies on the normality assumption and restricts the model into a single mechanism determining both the probability to demand a certain type of labor and the amount of this type of labor demanded. Technically, this means that $P(y > 0|\boldsymbol{x})$ and $E(y|\boldsymbol{x}, y > 0)$ are restricted to the same set of regressors $\boldsymbol{x}$ and that $\frac{\partial P(y>0|\boldsymbol{x})}{\partial x_j}$ and $\frac{\partial E(y|\boldsymbol{x},y>0)}{\partial x_j}$ have the same sign.

A small modification of the standard Tobit model, proposed by Deaton and Irish (1984), results in the P-Tobit model which allows for two types of zeros. The proportion of firms which potentially employ high-skilled (low-skilled) labor is p, while $1-p$ firms will never employ high-skilled (low-skilled) labor. The amount of high-skilled (low-skilled) labor demanded by potential employers of this type of labor is, thereupon, determined by the Tobit model. The log-likelihood for the P-Tobit model becomes:

$$\text{Log}L = \sum_0 ln \left[1 - p\Phi\left(\frac{\boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma}\right)\right] + \sum_+ ln \left[p\frac{1}{\sigma}\phi\left(\frac{y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma}\right)\right].$$

Further flexibility is added in more general two-part models introduced by Cragg (1971), the hurdle model and the double-hurdle model. Cragg (1971) presents a framework of models in which the size of y is allowed to be determined by different factors from those determining the probability of y being zero.

Hurdle models have become very popular because they are easy to implement in most statistical software packages, and they offer flexibility for a wide range of applications. In a first step, a firm has to make the decision either to employ a certain type of labor or not. This choice is indicated by a binary variable d. In the second step, a firm has to decide about the positive amount of high-skilled (low-skilled) labor. The first decision can, for example, be represented by a probit model while the second decision follows an appropriate model of positive outcome regression models (e.g. truncated regression, log-linear regression). The conditional density is then given by

$$f(y_i|\boldsymbol{x}_i) = \begin{cases} \Phi\left(-\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right) & \text{if} \quad y_i = 0, \\ \Phi\left(\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right) \cdot f(y_i|\boldsymbol{x}_i, d_i = 1) & \text{if} \quad y_i > 0. \end{cases}$$

A huge flexibility arises for the modeling of the positive outcomes. Either a standard regression model can be used or, if one wants to guarantee non-negativity of $E(y|\boldsymbol{x})$, truncated normal regression or log-linear regression can be applied.

If truncated normal regression is chosen in the second stage, the log-likelihood of the model becomes

$$\text{Log}L = \sum_{0} ln\left[\Phi\left(-\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right)\right] + \sum_{+} ln\left[\Phi\left(\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right) \cdot \frac{1}{\sigma}\frac{\phi(\frac{y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma})}{\Phi(\frac{\boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma})}\right].$$

Since the log-likelihood is separable, the parameters of the model can be estimated in two ways. One possibility is to apply a two-step procedure by first estimating a probit on the binary outcome of employing at least one high-skilled (low-skilled) worker and thereafter applying a truncated-normal regression on the positive outcomes. The second possibility is to maximize the log-likelihood function in one step (see McDowell (2003) for equivalency of these approaches). Since it is necessary to get access to individual likelihoods when conducting commonly used specification tests of non-nested models (e.g. the Vuong (1989) test), parameters of all econometric models are estimated by one-step maximum likelihood estimation even if a two-step procedure would have been possible to apply.

Cragg's (1971) double-hurdle model is a further generalization of the Tobit model. Like in the P-Tobit model, two hurdles have to be overcome in the double-hurdle model in order to observe a positive outcome. The firm has to desire a positive amount of high-skilled (low-skilled) labor and favorable circumstances have to arise in order to observe positive outcomes. The model becomes

$$
\begin{aligned}
d_i^* &= \boldsymbol{z}_i^{'}\boldsymbol{\gamma} + \epsilon_i, \qquad \epsilon_i \sim \mathcal{N}(0,1), \quad i = 1,2,\ldots,n, \\
y_i^* &= \boldsymbol{x}_i^{'}\boldsymbol{\beta} + u_i, \qquad u_i \sim \mathcal{N}(0,\sigma^2), \quad i = 1,2,\ldots,n, \\
y_i &= \begin{cases} y_i^* & \text{if} \quad y_i^* > 0 \quad \text{and} \quad d_i^* > 0, \\ 0 & \text{if} \quad y_i^* \leq 0 \quad \text{or} \quad d_i^* \leq 0, \end{cases}
\end{aligned}
$$

where u_i and ϵ_i are independently distributed. The log-likelihood function for the double-hurdle model becomes

$$
\begin{aligned}
\text{Log}L &= \sum_0 ln\left[\Phi\left(-\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right) + \Phi\left(\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right)\Phi\left(-\frac{\boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma}\right)\right] \\
&\quad + \sum_+ ln\left[\Phi\left(\boldsymbol{z}_i^{'}\boldsymbol{\gamma}\right)\frac{1}{\sigma}\phi\left(\frac{y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta}}{\sigma}\right)\right].
\end{aligned}
$$

In contrast to the hurdle model presented above, the likelihood of the double-hurdle model is not separable.[2]

Because the maximum likelihood estimations may be inconsistent if the common assumption of homoscedasticity is violated, heteroscedastic models are estimated by replacing σ with σ_i (Greene, 2003). Multiplicative heteroscedasticity is specified by $\sigma_i = \sigma \cdot exp\left(\boldsymbol{w}_i^{'}\boldsymbol{\alpha}\right)$. For all models, the null hypothesis of homoscedasticity ($\boldsymbol{\alpha} = 0$) is tested using Wald tests.

5.4.1.2 Specification tests

In order to select the model which best rationalizes heterogeneous labor demand in newly established firms, a sequential strategy is chosen. First, one needs to decide if a logarithmic transformation of the dependent variable might be necessary. Logarithmic transformations are often made in order to meet the assumption of the normal dis-

[2] Double-hurdle models are not implemented in Stata. The programming code used to obtain the double-hurdle estimator is presented in the Appendix.

tributed error terms. Therefore, a richer model is fitted which includes the logarithmic transformed model as a special case. The Box-Cox transformation given by

$$y_i^T = \begin{cases} \frac{y_i^\lambda - 1}{\lambda} & \text{if} \quad \lambda \neq 0, \\ ln(y_i) & \text{if} \quad \lambda = 0 \end{cases}$$

is a useful tool for choosing the right model. An estimate of the parameter λ close to zero indicates that the model should be estimated with the dependent variable logarithmic transformed. If $\lambda = 1$, i.e. $y^T = y_i - 1$, no transformation is necessary. A further advantage of the Box-Cox transformation is that it relaxes the normality assumption on the conditional distribution of the dependent variable. Box-Cox versions of the hurdle model and the double-hurdle model are estimated using maximum likelihood estimation. The log-likelihood function of the Box-Cox hurdle model is given by

$$\text{Log}L = \sum_0 ln\left[\Phi\left(-\boldsymbol{z}_i'\boldsymbol{\gamma}\right)\right] + \sum_+ ln\left[\Phi\left(\boldsymbol{z}_i'\boldsymbol{\gamma}\right) y_i^{\lambda-1}\frac{1}{\sigma}\phi\left(\frac{y_i^T - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma}\right)\right],$$

and the log-likelihood function of the Box-Cox double-hurdle is

$$\begin{aligned} \text{Log}L &= \sum_0 ln\left[1 - \Phi\left(\boldsymbol{z}_i'\boldsymbol{\gamma}\right)\Phi\left(\frac{\frac{1}{\lambda} + \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma}\right)\right] \\ &+ \sum_+ ln\left[\Phi\left(\boldsymbol{z}_i'\boldsymbol{\gamma}\right) y_i^{\lambda-1}\frac{1}{\sigma}\phi\left(\frac{y_i^T - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma}\right)\right]. \end{aligned}$$

Details on the Box-Cox double-hurdle model, which was first presented by Jones and Yen (2000), and its implementation in Stata can be found in the Appendix.

In a second step, the various censored regression models presented in section 5.4.1 are compared. Nested models can be compared using (adjusted) likelihood-ratio tests. The (unadjusted) likelihood-ratio used to test the P-Tobit model against the Tobit model is given by

$$LR \;=\; 2 \cdot [lnL(\theta_1) - lnL(\theta_2)], \qquad LR \sim \chi^2_{(1)}.$$

Vuong (1989) proposed to use an adjusted likelihood-ratio statistic. The adjusted likelihood-ratio statistic is given by

$$\widetilde{LR} \;=\; 2 \cdot [lnL(\theta_1) - lnL(\theta_2)] - (p-q), \qquad \widetilde{LR} \sim \chi^2_{(p-q)},$$

where p is the number of parameters in model 1 and q is the number of parameters of model 2. This statistic is used to test the double-hurdle model against the Tobit (and P-Tobit) model and to compare the hurdle model with the Tobit model.

A specification test for non-nested models proposed by Vuong (1989) is used to compare the hurdle model with the P-Tobit and to compare the double-hurdle model with the hurdle model. The Vuong statistic is given by

$$V \;=\; \frac{\sqrt{N}\bar{m}}{s_m}, \qquad V \overset{a}{\sim} \mathcal{N}(0,1)$$

with $\bar{m}$ and s_m being the mean and standard deviation of m_i, defined as $m_i = ln\left[\frac{f_1(y_i|\boldsymbol{x}_i)}{f_2(y_i|\boldsymbol{x}_i)}\right]$. The term $f_j(y_i|\boldsymbol{x}_i)$, for $j = 1, 2$, denotes the predicted probability that the random variable Y equals y_i. This statistic is used to test the null hypothesis that $E(m) = 0$. V is asymptotic normal distributed and bidirectional, i.e. the test favors model 1 if $V > 2$ and favors model 2 if $V < -2$. If $|V|<2$ neither of the models is favored (Greene, 2003).

Additionally, non-nested models can be compared using a non-parametric sign test proposed by Clarke (2003), which tests the null hypothesis $H_0 : \theta = 0$, where θ is the median log-likelihood ratio. The test statistic is the number of positive differences of the individual log-likelihoods ($C = \sum_i I_i\{f_1(y_i|\boldsymbol{x_i}) - f_2(y_i|\boldsymbol{x_i}) > 0\}$) and is distributed binominal $\mathcal{B}(C, p = 0.5)$. The intuition behind the test is, that if model 1 is be preferred to model 2, more than half the log-likelihood ratios should be greater than zero. The Clarke test can be shown to be asymptotically more efficient than the Vuong test if the distribution of the individual log-likelihoods is leptokurtic, i.e. exhibits thicker tails and higher peaks (e.g. double exponential), while the Vuong test is asymptotically more efficient than the Clarke test if the distribution of the individual log-likelihood ratios is mesokurtic (e.g. normal) or platykurtic (e.g. uniform) (Clarke, 2007).

Table 5.1: Specification tests - overview

Model	Test type	Restriction
Linear model vs.	Box-Cox	$\lambda = 1$ (linear)
log transformation		$\lambda = 0$ (log transformed)
P-Tobit vs. Tobit	LR	$p = 1$
Double-hurdle vs. Tobit	adj. LR	$\gamma_0 = \infty \wedge \gamma_1 = 0, \ldots, \gamma_k = 0$
Double-hurdle vs. P-Tobit	adj. LR	$\gamma_1 = 0, \ldots, \gamma_k = 0$
Hurdle vs. Tobit	adj. LR	$\frac{\beta}{\sigma} = \gamma$
Hurdle vs. P-Tobit	Vuong, Clarke	
Double-hurdle vs. hurdle	Vuong, Clarke	
Hurdle vs. double-hurdle	Vuong, Clarke	

Table 5.1 summarizes the approach for model selection and gives an overview of the specification tests and the restrictions to be tested.

5.4.2 The data and variables

Cross-sectional firm-level data of the first wave of the KfW/ZEW Start-Up Panel is used for investigating young firm's heterogeneous labor demand. The KfW/ZEW Start-Up Panel is a yearly survey of newly established firms and was launched in 2008. This project is a cooperation between the Centre of European Economic Research (ZEW), the KfW bank group, a state-owned German bank with tasks on behalf of the state, and the business information and debt collecting organization Creditreform, Germany's largest credit rating agency.

The data source for the first wave is a stratified[3] random draw of all firms founded as legally independent companies between 2005 and 2007. The survey was conducted via computer-assisted telephone interviews in 2008. More than 5,000 start-ups founded between 2005 and 2007 have been surveyed about the sociodemographical characteristics of the founders (the number of team members, educational background, professional ex-

[3]The sample is stratified by sector, year of foundation and KfW funding. Stratification criteria result in oversampling of firms operating in high-tech manufacturing and high-tech services as well as overrepresentation of firms which have received funds from KfW.

perience, etc.), the employment and financing structure, and other firm characteristics, for example innovation activities. Only firms with at least one employee in 2007, which is true for around 60 percent of all newly established firms in the sample, are included in the regressions. After dropping observations with missing data for the variables investigated, I end up with 2,988 observations.

Sectoral data about labor costs in 2007 for different skill groups are retrieved from the German Federal Statistical Office. Average sectoral wage for high-skilled, medium-skilled, and low-skilled workers are merged with firm-level data of the KfW/ZEW Start-Up Panel according to a firm's 3-digit NACE code.

Even if they employ at least one person besides the founders, newly established firms are relatively small. The mean number of employees, excluding the founders, is 5.5 persons. The median number of employees is 3. If founders are included, on average 6.9 persons work in a young firm of the sample. The median number of employees including the founders is 4. A summarizing description with descriptive statistics of all variables included in the econometric analysis is provided in Table 5.2. The variables are chosen according to the theoretical and conceptual considerations derived in Section 5.1 and 5.3.

Since I have no information about firm-level labor costs, I use employment shares instead of factor cost shares as dependent variables. This approach is common in the empirical literature investigating heterogeneous labor demand although it is less appropriate theoretically. But using employment shares instead of cost shares has the advantage to be able to decompose the effect of certain regressors (e.g. technology, human capital) into a relative wage component and a relative employment component (see Chennells and van Reenen, 2002). The average share of high-skilled employees in young firms of the sample is about 12.5 percent. Low-skilled employees account on average for 28.2 percent of all employees. Consequently, the majority of jobs created in young firms requires a medium skill-level.
As expected, the data exhibits a high number of zero values. About 81 percent of all firms in the sample do not employ any high-skilled employees, which amounts to 2,430 observations. Excess zeros are also highly present in case of the number of low-skilled employees. In total, 1,821 firms (61 percent) do not employ any low-skilled employees.

Price sensitivity is captured by including the logarithm of relative wages at the sectoral level (NACE 3-digit).

Table 5.2: Description of the variables included in the estimations

Variable	Description	Mean	Std. dev.
Dependent variables			
S_H	Share of high-skilled employees	0.125	0.296
S_L	Share of medium-skilled employees	0.282	0.403
Independent variables			
$Log(\frac{H}{M})$	Logarithm of $\left(\frac{\text{labor costs high-skilled}}{\text{labor costs medium-skilled}}\right)$	0.569	0.117
$Log(\frac{L}{M})$	Logarithm of $\left(\frac{\text{labor costs low-skilled}}{\text{labor costs medium-skilled}}\right)$	-0.326	0.160
$Log(L_{2007})$	Logarithm of the number of employees (with founders)	1.548	0.745
$Log(K)$	Logarithm of firm's capital stock	10.586	3.173
Miss $log(K)$	Missing capital stock	0.132	0.338
Human Capital - professional experience			
Log(industry exp.)	Logarithm of years of experience in the same industry	2.329	1.700
Entr. exp. (n. s.)	Entrepreneurial experience (not successful). The founder's previous business has become insolvent or has been liquidated.	0.123	0.329
Entr. exp. (s.)	Entrepreneurial experience (successful). The founder's previous business still exists.	0.253	0.435
Human Capital - highest educational degree			
Without	No professional education	0.028	0.166
Vocational training	Completed vocational training	0.315	0.464
Master craftsman	Completed professional school, e.g. master craftsman diploma	0.261	0.439
University degree	Completed higher education, university or university of applied science	0.360	0.480
Ph.D.	Completed postgraduate education	0.036	0.187
R&D	Firm is conducting R&D continuously.	0.171	0.377
Team	Firm was founded by a team of founders.	0.310	0.463
Het. educ. degr.	Founders have different educational degrees.	0.093	0.291
Year of foundation			
Founded 2006	Firm started operations in 2005.	0.352	0.478
Founded 2006	Firm started operations in 2006.	0.353	0.478
Founded 2007	Firm started operations in 2007.	0.295	0.456
Industry			
High-tech manuf.	Industry: High-tech manufacturing	0.131	0.338
Software	Industry: Software	0.155	0.362
Techn.-int. serv.	Industry: Technology-intensive services	0.070	0.255
Knowl.-int serv.	Industry: Knowledge-intensive services	0.062	0.240
Low-tech manuf.	Industry: Low-tech manufacturing	0.130	0.336
Busin.-related serv.	Industry: Business-related services	0.060	0.237
Cons.-related serv.	Industry: Consumer-related services	0.132	0.339
Construction	Industry: Construction	0.116	0.320
Retail and wholesale	Industry: Retail and wholesale	0.145	0.352

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

The output, which should be included in the regressions according to the theoretical model, is difficult to measure in young firms. Newly established firms often do not realize sales in the first years. Therefore, a measure which relies on turnover figures might not be the right measure for output in case of young firms. Furthermore, often firms are reluctant to provide data about sales or profit either because they do not like to reveal sensitive data or because they do not remember the exact number. For this reason, I proxy output by the total number of employees (including the founders) which should reflect the expectations about the future value added created by the firm.

The capital stock is calculated via summing up all investments made since foundation and assuming an annual depreciation rate of 6 percent. Yearly data on capital investment is missing for a number of firms. In order not to lose a lot of observations because of capital stock missings, observations with capital stock missings are included in the analysis. A particular value is assigned to these observations and they are marked using a dummy variable *(miss* $log(K)$*)*.[4]

Concerning human capital, I distinguish between professional experience as a measure of specific human capital and the educational degree of the founders as a measure of generic human capital. Professional experience is measured in two dimensions: industry experience and entrepreneurial experience (previous self-employment). Industry experience is measured by the years of industry experience of the founder. If the start-up was established by a team of founders the years of industry experience are retrieved for the founder with the longest industry experience. Entrepreneurial experience is further divided into successful entrepreneurial experience (the previous business still exists) and entrepreneurial experience which was not successful (the previous business has either become insolvent or has been voluntarily closed).

With respect to professional education, I distinguish between five educational degrees. In case of team foundations the highest educational degree within the team of founders is chosen. If the founder did not complete any kind of professional training after school, he is assigned the lowest level of education (*without*). A common type of professional education in Germany is company-based vocational training (*vocational training*). The German apprenticeship system is a dual system. Apprentices are trained both in a vocational school and the firm, and they receive a certificate after completing their training. Having completed vocational training serves as reference category in the

[4] This method is called *dummy variable adjustment* or *missing indicator method* and is frequently used in econometric analysis (Allison, 2001). A value of $log(0.5)$ was assigned to these observations.

regressions. After completing vocational training further education is provided by professional schools. In those schools, craftsmen or technicians get further training. A certificate issued after passing master craftsman exams is required in some professions in order to establish a business or to train apprentices (*master craftsman*). Higher education at universities is captured by two dummy variables. *University degree* denotes that the highest educational degree of the founder is a university degree which is comparable to a bachelor's or master's degree. *Ph.D.* denotes that the founder has additionally completed postgraduate or postdoctoral studies afterwards.

As a proxy for the stock of knowledge capital, a dummy variable is used which indicates if the start-up is conducting research and development (*R&D*) continuously. If a firm claims to conduct R&D continuously, one can expect that the firm has accumulated a larger stock of knowledge capital than firms which do not conduct any R&D activities or only conduct R&D infrequently. The hypothesis of a skill-biased technological change is tested for newly established firms by means of including this dummy variable.

Furthermore, a set of control variables is included in the regressions which are also expected to affect the structure of the workforce in young firms. In order to capture differences in heterogeneous labor demand between foundations of a single person and team foundations, I include a dummy variable which indicates if the start-up was established by a team of founders (*team*). Because of financial pooling, teams should be less financially restricted. Moreover, ability pooling is expected to take place in case of team foundations. Founders skills are expected to show up more breadth. According to the theory of Lazear (2004), a more general skill-profile is expected to result in higher profits. But higher expected profits should likewise also affect a firm's heterogeneous labor demand. Heterogeneity of the founders is explicitly captured by a dummy variable which indicates if there are several educational degrees within the team of founders (*het. educ. degr.*). Furthermore, I control for the year of foundation and the industry. For the hurdle and double-hurdle models, the same set of regressors is chosen for each stage, i.e. $\boldsymbol{x}_i = \boldsymbol{z}_i$.

Firm size, industry, and the year of foundation are chosen as variables potentially determining the heteroscedasticity. Wald tests on joint significance of these variables are performed in order to test the null hypothesis of homoscedasticity.

5.4.3 Estimation results

First, the model specification is examined. Heteroscedastic estimation of all models are conducted and joint significance of the variables explaining the heteroscedasticity is tested. Results of the Wald tests are presented in Table 5.3. It turns out that homoscedasticity can be rejected for both the share of high-skilled employees and the share of low-skilled employees in all models. Therefore, I stay with heteroscedastic estimation.

Table 5.3: Wald test on joint significance of variables included in $\mathbf{w}_i$

Model	high-skilled		low-skilled	
	Test value $\chi^2(11)$	p-value	Test value $\chi^2(11)$	p-value
Tobit	100.94	[0.000]	277.25	[0.000]
P-Tobit	368.01	[0.000]	52.80	[0.000]
Hurdle (Trunc. normal)	68.04	[0.000]	203.32	[0.000]
Hurdle (Log-linear)	410.85	[0.000]	133.94	[0.000]
Box-Cox hurdle	111.69	[0.000]	42.85	[0.000]
Double-hurdle	58.09	[0.000]	86.35	[0.000]
Box-Cox double-hurdle	49.99	[0.000]	91.59	[0.000]

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

In order to asses the need of logarithmic transformation of the dependent variable, Box-Cox regressions have been made. Estimates of the parameter λ are presented in Table 5.4. Furthermore, Wald tests of the null hypothesis $\lambda = 0$ (logarithmic transformation) and $\lambda = 1$ (linear model) have been conducted. The null hypothesis of $\lambda = 0$ can be rejected for both the hurdle model and the double-hurdle model. Accordingly, the null hypothesis of $\lambda = 1$ cannot be rejected in case of low-skilled workers in the hurdle model and in case of high-skilled workers in the double-hurdle model. However, $\lambda = 1$ can be rejected on the 10 percent significance level in case of high-skilled workers in the hurdle model and even on the 5 percent significance level in case of low-skilled workers in the double-hurdle model. All in all, there seems to be no need of logarithmic transformation. Therefore, a truncated normal regression is preferred to a log-linear regression as second stage in the hurdle model. Similarly, the dependent variables have not been transformed in the double-hurdle model. Full results of the Box-Cox hurdle model and the Box-Cox double-hurdle model can be found in Tables 5.12 and 5.13 and Table 5.15 in the Appendix.

Table 5.4: Results of the Box-Cox models - estimates of λ and Wald tests

Model	high-skilled		low-skilled	
	Test-value ($\chi^2(1)$)	P-value	Test-value ($\chi^2(1)$)	P-value
Box-Cox Hurdle	$\hat{\lambda} = 0.629$		$\hat{\lambda} = 0.893$	
H0: $\lambda = 0$	8.13	[0.004]	16.99	[0.000]
H0: $\lambda = 1$	2.82	[0.093]	0.24	[0.621]
Box-Cox Double-Hurdle	$\hat{\lambda} = 1.201$		$\hat{\lambda} = 1.433$	
H0: $\lambda = 0$	18.92	[0.000]	68.50	[0.000]
H0: $\lambda = 1$	0.53	[0.467]	6.25	[0.012]

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.5 displays the results of the specification tests. Likelihood-ratio tests indicate that the P-Tobit is preferred to the Tobit model and that the double-hurdle model is preferred to both the Tobit and the P-Tobit model. Furthermore, the hurdle model is preferred to the Tobit model. The tests for non-nested models (Vuong and Clarke tests) show that the hurdle model with truncated-normal regression as second stage is also preferred to the P-Tobit model. However, there is no clear sign whether to prefer either the double-hurdle or the hurdle-model. In case of the share of high-skilled employees, the double-hurdle model seems to be preferred while, in case of low-skilled employees, the hurdle model performs better.

Therefore, both the estimation results of the hurdle model with truncated normal regression as second stage and the results of the double-hurdle model are presented below. Estimation results for the Tobit, the P-Tobit, the hurdle models with logarithmic and Box-Cox transformation, and the Box-Cox double-hurdle model can be found in the Appendix.

Let us now have a look at the estimation results of the hurdle and double-hurdle models. The estimated coefficients can be found in Table 5.6 for the hurdle model and in Table 5.7 for the double-hurdle models.

In case of separable hurdle models the probability is estimated to employ at least one high-skilled (low-skilled) employee using probit regressions in the first hurdle. The second hurdle estimates the share of high-skilled (low-skilled) employees given that the firm employs at least one high-skilled (low-skilled) employee using a truncated normal regression. Interpretation of the coefficients on their own is limited. However, at

Table 5.5: Specification tests - results

Model	Test type	high-skilled Test value	high-skilled P-value	low-skilled Test value	low-skilled P-value
P-Tobit vs. Tobit	LR	32.3	[0.000]	690.0	[0.000]
Double-hurdle vs. Tobit	adj. LR	500.1	[0.000]	1101.6	[0.000]
Double-hurdle vs. P-Tobit	adj. LR	468.8	[0.000]	412.5	[0.000]
Hurdle vs. Tobit	adj. LR	482.7	[0.000]	1176.8	[0.000]
Hurdle vs. P-Tobit	Vuong	13.1	[0.000]	12.0	[0.000]
	Clarke	2106	[0.000]	1938	[0.000]
Double-hurdle vs. hurdle	Vuong	1.6	[0.060]	-4.4	[1.000]
	Clarke	1638	[0.000]	1444	[0.968]
Hurdle vs. double-hurdle	Vuong	-1.6	[0.940]	4.4	[0.000]
	Clarke	1350	[1.000]	1544	[0.035]

Notes: [0.000] indicates that the first model is preferred, e.g. P-Tobit is preferred to Tobit.
Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

least the direction of the effect in the Probit part can be seen immediately from the corresponding coefficient's sign. Furthermore, for variables which are included in both the second stage equation and the heteroscedastic equation, the marginal effects on the conditional mean may not be directly related to the corresponding coefficient in the second stage (Yen and Su, 1995). Interpretation of the coefficients of the double-hurdle model is even more difficult since the model is not separable, and the first and the second hurdle determine the probability of a positive outcome of the dependent variable in conjuncture. Marginal effects have to be calculated.

When interpreting the results, one can distinguish three possible effects: the effect of a variable on the probability to employ at least one person of the respective skill-group ($\frac{\partial P(y>0)}{\partial x_j}$), the conditional effect of a variable on the share of workers in a certain skill-group given the firm employs at least one person in this skill-group ($\frac{\partial E(y|y>0)}{\partial x_j}$) and the unconditional effect of a variable on the share of workers in a certain skill-group ($\frac{\partial E(y)}{\partial x_j}$) (Yen and Su, 1995; Burke, 2009). Since I chose the same set of regressors in each stage ($\boldsymbol{x}_i = \boldsymbol{z}_i$), the probability of a non-zero outcome in the hurdle model is given by

$$P^H(y_i > 0|\boldsymbol{x}_i) = \Phi(\boldsymbol{x}_i^{'}\boldsymbol{\gamma}).$$

Likewise, the probability for positive outcomes in the double-hurdle model is given by

$$P^{DH}(y_i > 0|\boldsymbol{x}_i) = \Phi(\boldsymbol{x}_i^{'}\boldsymbol{\gamma}) \cdot \Phi(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i).$$

In both the hurdle and the double-hurdle model, the conditional mean of y_i is given by

$$E^H(y_i|y_i > 0, \boldsymbol{x}_i) = E^{DH}(y_i|y_i > 0, \boldsymbol{x}_i) = \boldsymbol{x}_i^{'}\boldsymbol{\beta} + \sigma_i \cdot \lambda\left(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i\right),$$

where $\lambda(c)$ denotes the inverse Mills ratio $\lambda(c) = \phi(c)/\Phi(c)$.

Accordingly, the unconditional mean of y_i in the hurdle model is

$$E^H(y_i|\boldsymbol{x}_i) = \Phi(\boldsymbol{x}_i^{'}\gamma)\left[\boldsymbol{x}_i^{'}\boldsymbol{\beta} + \sigma_i \cdot \lambda\left(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i\right)\right],$$

while it is

$$E^{DH}(y_i|\boldsymbol{x}_i) = \Phi(\boldsymbol{x}_i^{'}\boldsymbol{\gamma}) \cdot \Phi(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\left[\boldsymbol{x}_i^{'}\boldsymbol{\beta} + \sigma_i \cdot \lambda\left(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i\right)\right]$$

in case of the double-hurdle model.

For continuous variables, marginal effects are obtained by differentiating expected outcomes. The marginal effect on the probability to employ a person of the respective skill-group is calculated as follows [5]

$$\frac{\partial P^H(y_i > 0|\boldsymbol{x}_i)}{\partial x_{ij}} = \phi(\boldsymbol{x}_i^{'}\boldsymbol{\gamma})\gamma_j.$$

The conditional effect of a continuous variable on the share of workers in a certain skill-group, given the firm employs at least one person in this skill-group, amounts to

$$\begin{aligned}\frac{\partial E^H(y_i|y_i > 0, \boldsymbol{x}_i)}{\partial x_{ij}} &= \beta_j + \lambda(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\frac{\partial \sigma_i}{\partial x_{ij}} - \lambda(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\left[\beta_j - (\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\frac{\partial \sigma_i}{\partial x_{ij}}\right] \\ &\quad \cdot \left[(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i) + \lambda(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\right].\end{aligned}$$

[5] In deriving marginal effects, I generalize the results of Burke (2009) to the heteroscedastic case. Implementing the calculating of marginal effects in Stata, I fall back on the implementation proposed by Burke (2009).

Table 5.6: Two-step hurdle model of heterogeneous labor demand

	Share of high-skilled employees			
	Probit		Trunc. Reg.	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	-0.785*	(0.427)	0.195	(0.196)
$Log(\frac{L}{M})$	-0.578*	(0.347)	-0.127	(0.139)
$Log(L_{2007})$	0.358***	(0.068)	-0.335***	(0.090)
$Log(K)$	0.022*	(0.012)	-0.005	(0.004)
Miss $log(K)$	0.180	(0.176)	-0.051	(0.048)
Human Capital - professional experience				
Log(industry exp.)	0.059**	(0.025)	-0.008	(0.015)
Entr. exp. (n. s.)	0.120*	(0.063)	0.005	(0.025)
Entr. exp. (s.)	0.151***	(0.056)	0.007	(0.027)
Human Capital - highest educational degree$^{(1)}$				
Without	-0.438*	(0.226)	0.073	(0.185)
Master craftsman	-0.246**	(0.113)	0.045	(0.056)
University degree	0.646***	(0.102)	0.097	(0.062)
Ph.D.	1.002***	(0.147)	0.167**	(0.066)
R&D	0.543***	(0.079)	0.059**	(0.023)
Team	0.092	(0.092)	0.141***	(0.054)
Het. educ. degr.	-0.239*	(0.127)	-0.100**	(0.045)
Year of foundation$^{(2)}$				
Founded 2006	-0.006	(0.073)	-0.000	(0.026)
Founded 2007	-0.054	(0.082)	-0.026	(0.033)
Industry$^{(3)}$				
HT manuf.	0.526***	(0.126)	0.053	(0.082)
Techn.-int. serv.	0.728***	(0.106)	0.077	(0.078)
Software	0.716***	(0.135)	0.127	(0.092)
Knowl.-int. serv.	0.881***	(0.125)	0.041	(0.092)
Low-tech manuf.	0.158	(0.110)	-0.070	(0.079)
Busin.-rel. serv.	0.341**	(0.162)	0.090	(0.082)
Cons.-rel. serv.	-0.255*	(0.152)	0.006	(0.103)
Construction	0.063	(0.172)	0.004	(0.072)
Constant	-2.460***	(0.291)	0.922***	(0.254)
σ_i				
Test on joint sign. of var. in $\mathbf{w}_i$ ($\chi^2(11)$)	68.04*** [0.000]			
$Log(\sigma)$	-2.163*** (0.372)			
ll	-1037			
Observations	2988			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses.
References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.6 – Continued

	Share of low-skilled employees			
	Probit		Trunc. Reg.	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	0.762	(0.501)	0.000	(0.073)
$Log(\frac{L}{M})$	0.542*	(0.318)	0.043	(0.052)
$Log(L_{2007})$	0.373***	(0.041)	-0.413***	(0.051)
$Log(K)$	-0.022**	(0.010)	-0.002	(0.002)
Miss $log(K)$	-0.347***	(0.113)	-0.027	(0.022)
Human Capital - professional experience				
Log(industry exp.)	-0.057***	(0.015)	-0.005	(0.004)
Entr. exp. (n. s.)	0.040	(0.063)	-0.031	(0.027)
Entr. exp. (s.)	-0.098	(0.063)	-0.007	(0.018)
Human Capital - highest educational degree$^{(1)}$				
Without	0.477***	(0.151)	0.046**	(0.021)
Master craftsman	-0.285***	(0.079)	-0.037*	(0.020)
University degree	-0.392***	(0.071)	-0.051***	(0.016)
Ph.D.	-0.562***	(0.142)	-0.125***	(0.047)
R&D	-0.155**	(0.062)	-0.002	(0.021)
Team	-0.269***	(0.066)	0.095***	(0.027)
Het. educ. degr.	0.136	(0.087)	0.081**	(0.037)
Year of foundation$^{(2)}$				
Founded 2006	-0.028	(0.052)	0.027	(0.018)
Founded 2007	-0.134**	(0.057)	0.003	(0.018)
Industry$^{(3)}$				
HT manuf.	-0.266*	(0.139)	-0.108***	(0.035)
Techn.-int. serv.	-0.288**	(0.134)	-0.039**	(0.020)
Software	-0.118	(0.160)	-0.077***	(0.024)
Knowl.-int. serv.	-0.546**	(0.217)	-0.009	(0.024)
Low-tech manuf.	-0.144	(0.136)	0.005	(0.032)
Busin.-rel. serv.	0.137	(0.169)	-0.011	(0.036)
Cons.-rel. serv.	0.170	(0.181)	0.039*	(0.021)
Construction	-0.282*	(0.146)	-0.081***	(0.018)
Constant	-0.227	(0.337)	1.366***	(0.075)
σ_i				
Test on joint sign. of var. in $\mathbf{w}_i$ ($\chi^2(11)$)	203.32*** [0.000]			
$Log(\sigma)$	-2.486*** (0.118)			
ll	-1732			
Observations	2988			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses.
References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.7: Double-hurdle model of heterogeneous labor demand

	Share of high-skilled employees			
	Hurdle 1		Hurdle 2	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	-0.710	(0.459)	0.175	(0.182)
$Log(\frac{L}{M})$	-0.425	(0.367)	-0.211	(0.128)
$Log(L_{2007})$	0.612***	(0.062)	-0.293***	(0.048)
$Log(K)$	0.020*	(0.012)	-0.004	(0.004)
Miss $log(K)$	0.156	(0.179)	-0.052	(0.052)
Human Capital - professional experience				
Log(industry exp.)	0.068***	(0.026)	-0.007	(0.013)
Entr. exp. (n. s.)	0.132**	(0.066)	-0.003	(0.026)
Entr. exp. (s.)	0.144**	(0.058)	0.016	(0.025)
Human Capital - highest educational degree(1)				
Without	-0.516**	(0.241)	0.084	(0.169)
Master craftsman	-0.278**	(0.113)	0.037	(0.052)
University degree	0.642***	(0.112)	0.110*	(0.057)
Ph.D.	1.051***	(0.159)	0.171***	(0.058)
R&D	0.518***	(0.078)	0.069***	(0.024)
Team	-0.003	(0.090)	0.119***	(0.036)
Het. educ. degr.	-0.246*	(0.131)	-0.092**	(0.040)
Year of foundation(2)				
Founded 2006	-0.012	(0.075)	0.003	(0.026)
Founded 2007	-0.022	(0.089)	-0.041	(0.029)
Industry(3)				
HT manuf.	0.501***	(0.138)	0.085	(0.093)
Techn.-int. serv.	0.770***	(0.121)	0.099	(0.086)
Software	0.777***	(0.145)	0.136	(0.093)
Knowl.-int. serv.	0.883***	(0.143)	0.064	(0.102)
Low-tech manuf.	0.208*	(0.115)	-0.049	(0.090)
Busin.-rel. serv.	0.484**	(0.196)	0.078	(0.091)
Cons.-rel. serv.	-0.243	(0.160)	-0.035	(0.114)
Construction	0.043	(0.185)	0.031	(0.086)
Constant	-2.778***	(0.266)	0.819***	(0.200)
σ_i				
Test on joint sign. of var. in $\mathbf{w}_i$ ($\chi^2(11)$)	58.09*** [0.000]			
$Log(\sigma)$	-1.906*** (0.251)			
ll	-1028			
Observations	2988			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses.
References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.7 – Continued

	Share of low-skilled employees			
	Hurdle 1		Hurdle 2	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	0.667	(0.524)	0.028	(0.072)
$Log(\frac{L}{M})$	0.503	(0.325)	0.060	(0.055)
$Log(L_{2007})$	0.585***	(0.044)	-0.343***	(0.047)
$Log(K)$	-0.025**	(0.011)	-0.003	(0.002)
Miss $log(K)$	-0.390***	(0.131)	-0.034	(0.023)
Human Capital - professional experience				
Log(industry exp.)	-0.053***	(0.015)	-0.007	(0.004)
Entr. exp. (n. s.)	0.023	(0.067)	-0.029	(0.028)
Entr. exp. (s.)	-0.125*	(0.068)	-0.002	(0.019)
Human Capital - highest educational degree$^{(1)}$				
Without	0.501***	(0.163)	0.043**	(0.021)
Master craftsman	-0.310***	(0.079)	-0.039*	(0.022)
University degree	-0.404***	(0.073)	-0.060***	(0.017)
Ph.D.	-0.521***	(0.155)	-0.144***	(0.052)
R&D	-0.157**	(0.069)	-0.003	(0.020)
Team	-0.362***	(0.074)	0.082***	(0.026)
Het. educ. degr.	0.104	(0.092)	0.078**	(0.034)
Year of foundation$^{(2)}$				
Founded 2006	-0.055	(0.053)	0.033*	(0.019)
Founded 2007	-0.163***	(0.061)	0.009	(0.018)
Industry$^{(3)}$				
HT manuf.	-0.232	(0.150)	-0.129***	(0.039)
Techn.-int. serv.	-0.273*	(0.140)	-0.045**	(0.020)
Software	-0.105	(0.164)	-0.086***	(0.026)
Knowl.-int. serv.	-0.548**	(0.216)	-0.013	(0.025)
Low-tech manuf.	-0.146	(0.139)	-0.004	(0.034)
Busin.-rel. serv.	0.154	(0.178)	0.000	(0.034)
Cons.-rel. serv.	0.146	(0.189)	0.044**	(0.020)
Construction	-0.300**	(0.147)	-0.092***	(0.018)
Constant	-0.351	(0.343)	1.294***	(0.074)
σ_i				
Test on joint sign. of var. in $\mathbf{w}_i$ ($\chi^2(11)$)	86.35*** [0.000]			
$Log(\sigma)$	-2.392*** (0.137)			
ll	-1769			
Observations	2988			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses.
References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

As in McDonald and Moffitt (1980) the unconditional marginal effect can be decomposed in two parts, which have been already derived above:

$$\frac{\partial E^H(y_i|\boldsymbol{x}_i)}{\partial x_{ij}} = \frac{\partial P_H(y_i > 0|\boldsymbol{x}_i)}{\partial x_{ij}} \cdot E_H(y_i|y_i > 0, \boldsymbol{x}_i) + P^H(y_i > 0|\boldsymbol{x}_i) \cdot \frac{\partial E_H(y_i|y_i > 0, \boldsymbol{x}_i)}{\partial x_{ij}}$$

Similarly, marginal effects in the double-hurdle models are obtained (see Yen and Su, 1995):

$$\begin{aligned}
\frac{\partial P^{DH}(y_i > 0|\boldsymbol{x}_i)}{\partial x_{ij}} &= \phi(\boldsymbol{x}_i^{'}\boldsymbol{\gamma})\Phi(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\gamma_j \\
&\quad +\phi(\boldsymbol{x}_i^{'}\boldsymbol{\gamma})\Phi(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\sigma_i^{-1} \cdot \left[\beta_j - (\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\frac{\partial \sigma_i}{\partial x_{ij}}\right], \\
\frac{\partial E^{DH}(y_i|y_i > 0, \boldsymbol{x}_i)}{\partial x_{ij}} &= \beta_j + \lambda(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\frac{\partial \sigma_i}{\partial x_{ij}} \\
&\quad -\lambda(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\left[\beta_j - (\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\frac{\partial \sigma_i}{\partial x_{ij}}\right] \cdot \left[(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i) + \lambda(\boldsymbol{x}_i^{'}\boldsymbol{\beta}/\sigma_i)\right], \\
\frac{\partial E^{DH}(y_i|\boldsymbol{x}_i)}{\partial x_{ij}} &= \frac{\partial P^{DH}(y_i > 0|\boldsymbol{x}_i)}{\partial x_{ij}} \cdot E^{DH}(y_i|y_i > 0, \boldsymbol{x}_i) \\
&\quad +P^{DH}(y_i > 0|\boldsymbol{x}_i) \cdot \frac{\partial E^{DH}(y_i|y_i > 0, \boldsymbol{x}_i)}{\partial x_{ij}}.
\end{aligned}$$

For variables not included in the heteroscedastic equation, $\partial \sigma_i / \partial x_{ij} = 0$ and the expressions can be simplified accordingly.

Discrete differences for both the hurdle and the double-hurdle model are calculated in case of factor variables. This is the discrete change in $P(y_i > 0)$, $E(y_i|y_i > 0)$ and $E(y_i)$ when the value of the variable shifts from zero to one, holding all the other variables constant.

$$\begin{aligned}
\frac{\mathrm{d}P(y_i > 0)}{\mathrm{d}x_{ij}} &= P(y_i > 0|x_{ij} = 1, \boldsymbol{x_i}) - P(y_i > 0|x_{ij} = 0, \boldsymbol{x_i}) \\
\frac{\mathrm{d}E(y_i|y_i > 0)}{\mathrm{d}x_{ij}} &= E(y_i|y_i > 0, x_{ij} = 1, \boldsymbol{x_i}) - E(y_i|y_i > 0, x_{ij} = 0, \boldsymbol{x_i}) \\
\frac{\mathrm{d}E(y_i)}{\mathrm{d}x_{ij}} &= E(y_i|x_{ij} = 1, \boldsymbol{x_i}) - E(y_i|x_{ij} = 0, \boldsymbol{x_i})
\end{aligned}$$

Marginal effects and discrete differences are obtained at the mean of the explanatory variables. Standard errors are calculated using the delta method, a common approximation appropriate in large samples. Results for the hurdle models are presented in Tables 5.8 and 5.9. Marginal effects for the double-hurdle models can be found in Tables 5.10 and 5.11.

All in all, the effects do not substantially differ between the hurdle and the double-hurdle model. With respect to the relative wage of high-skilled workers ($log\left(\frac{H}{M}\right)$), I find a small negative and weakly significant effect on the probability to employ high-skilled workers. This is consistent with traditional microeconomic theory. If the wage level of high-skilled workers increases relative to that of medium-skilled workers, the probability to employ high-skilled workers decreases. However, the relative wage seems to have no effect on the conditional and unconditional mean of the share of high-skilled workers. The effect is also not present in case of the double-hurdle model or the share of low-skilled workers as dependent variable.

The relative wage of low-skilled workers ($log\left(\frac{L}{M}\right)$) is found to negatively affect the probability to employ high-skilled workers and the unconditional mean of the share of high-skilled workers. The other way around, it affects the probability to employ low-skilled workers and the unconditional mean of low-skilled workers positively. This seems to be counterintuitive at a first view but might be an indication of complex complementarities between high-skilled, medium-skilled and low-skilled workers. This effect is not robust, since the marginal effect in the double-hurdle model turns out not to be significantly different from zero.

Firm size ($log(L_{2007})$) has in all models a positive impact both on the probability to employ at least one high-skilled worker and on the probability to employ at least one low-skilled worker. However, in the second hurdle, both the share of high-skilled workers and the share of low-skilled workers are negatively correlated with firm size. This indicates that as firm size increases, the probability to employ at least one person of a specific skill group increases for all skill groups, but most of the jobs created when firm size increases require a medium level of education.

The coefficient concerning the physical capital stock ($log(K)$) of the firm is consistent with the hypothesis of capital skill complementarity (Griliches, 1969). For the share of high-skilled employees, a higher capital stock is related to a higher probability of employing high-skilled workers in both the hurdle model and the double-hurdle model.

Table 5.8: Marginal effects of the hurdle model (share of high-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y\|y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$Log(\frac{H}{M})$	-0.074	(0.056)	0.188	(0.189)	-0.157*	(0.085)
$Log(\frac{L}{M})$	-0.085*	(0.049)	-0.122	(0.134)	-0.116*	(0.070)
$Log(L_{2007})$	0.007	(0.015)	-0.312***	(0.084)	0.072***	(0.014)
$Log(K)$	0.002	(0.002)	-0.005	(0.004)	0.004*	(0.002)
Human Capital - professional experience						
Log(industry exp.)	0.006**	(0.003)	-0.008	(0.015)	0.012**	(0.005)
Entr. exp. (n. s.)	0.019*	(0.010)	0.002	(0.012)	0.025*	(0.014)
Entr. exp. (s.)	0.023***	(0.009)	0.003	(0.011)	0.032**	(0.012)
Human Capital - highest educational degree(1)						
Without	-0.046**	(0.021)	0.040	(0.110)	-0.068***	(0.026)
Master craftsman	-0.031**	(0.015)	0.020	(0.026)	-0.046**	(0.020)
University degree	0.109***	(0.020)	0.041	(0.029)	0.144***	(0.025)
Ph.D.	0.258***	(0.047)	0.100**	(0.046)	0.304***	(0.056)
R&D	0.100***	(0.017)	0.029**	(0.012)	0.132***	(0.023)
Team	0.022	(0.017)	0.066**	(0.029)	0.019	(0.019)
Het. educ. degr.	-0.041**	(0.019)	-0.046**	(0.019)	-0.046**	(0.023)
Year of foundation(2)						
Founded in 2006	-0.001	(0.011)	-0.001	(0.011)	-0.001	(0.014)
Founded in 2007	-0.008	(0.011)	-0.002	(0.014)	-0.011	(0.016)
Industry(3)						
HT manuf.	0.099***	(0.024)	0.031	(0.047)	0.130***	(0.037)
Tech.-int. services	0.149***	(0.023)	0.055	(0.041)	0.189***	(0.033)
Software	0.162***	(0.036)	0.076	(0.056)	0.195***	(0.046)
Knowl.-int services	0.192***	(0.033)	0.029	(0.051)	0.254***	(0.046)
Low-tech manuf.	0.020	(0.017)	-0.026	(0.029)	0.034	(0.025)
Busin.-rel. serv.	0.071**	(0.034)	0.070*	(0.041)	0.081*	(0.044)
Cons.-rel. serv.	-0.031*	(0.018)	0.020	(0.052)	-0.046*	(0.024)
Construction	0.009	(0.024)	-0.005	(0.039)	0.013	(0.036)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.9: Marginal effects of the hurdle model (share of low-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y\|y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$Log(\frac{H}{M})$	0.190	(0.142)	0.000	(0.071)	0.291	(0.191)
$Log(\frac{L}{M})$	0.151*	(0.084)	0.042	(0.051)	0.207*	(0.121)
$Log(L_{2007})$	-0.055**	(0.025)	-0.390***	(0.049)	0.142***	(0.016)
$Log(K)$	-0.006**	(0.003)	-0.002	(0.002)	-0.008**	(0.004)
Human Capital - professional experience						
Log(industry exp.)	-0.016***	(0.004)	-0.005	(0.004)	-0.022***	(0.006)
Entr. exp. (n. s.)	0.006	(0.017)	-0.015	(0.012)	0.015	(0.024)
Entr. exp. (s.)	-0.029	(0.019)	-0.003	(0.008)	-0.037	(0.024)
Human Capital - highest educational degree$^{(1)}$						
Without	0.156***	(0.046)	0.025**	(0.012)	0.188***	(0.059)
Master craftsman	-0.085***	(0.022)	-0.015*	(0.008)	-0.106***	(0.029)
University degree	-0.117***	(0.019)	-0.019***	(0.006)	-0.146***	(0.026)
Ph.D.	-0.155***	(0.028)	-0.056***	(0.018)	-0.190***	(0.040)
R&D	-0.044***	(0.017)	-0.001	(0.010)	-0.058**	(0.023)
Team	-0.061***	(0.019)	0.044***	(0.013)	-0.101***	(0.024)
Het. educ. degr.	0.056**	(0.027)	0.046**	(0.022)	0.049	(0.032)
Year of foundation$^{(2)}$						
Founded in 2006	-0.004	(0.014)	0.011	(0.008)	-0.011	(0.020)
Founded in 2007	-0.037**	(0.016)	0.003	(0.008)	-0.050**	(0.021)
Industry$^{(3)}$						
HT manuf.	-0.088***	(0.034)	-0.046***	(0.011)	-0.098**	(0.049)
Tech.-int. serv.	-0.087***	(0.034)	-0.023**	(0.011)	-0.106**	(0.047)
Software	-0.048	(0.042)	-0.041***	(0.012)	-0.044	(0.059)
Knowl.-int serv.	-0.142***	(0.049)	-0.002	(0.009)	-0.187***	(0.064)
Low-tech manuf.	-0.042	(0.039)	-0.003	(0.016)	-0.054	(0.050)
Busin.-rel. serv.	0.045	(0.050)	0.012	(0.016)	0.053	(0.066)
Cons.-rel. serv.	0.064	(0.056)	0.033***	(0.011)	0.066	(0.071)
Construction	-0.090**	(0.036)	-0.040***	(0.008)	-0.103**	(0.051)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.10: Marginal effects of the double-hurdle model (share of high-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y\|y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$Log(\frac{H}{M})$	-0.067	(0.059)	0.167	(0.173)	-0.148	(0.097)
$Log(\frac{L}{M})$	-0.081	(0.052)	-0.200	(0.122)	-0.092	(0.078)
$Log(L_{2007})$	0.040***	(0.010)	-0.269***	(0.044)	0.124***	(0.013)
$Log(K)$	0.002	(0.002)	-0.004	(0.004)	0.004*	(0.002)
Human Capital - professional experience						
Log(industry exp.)	0.008**	(0.003)	-0.007	(0.012)	0.014***	(0.005)
Entr. exp. (n. s.)	0.015	(0.009)	-0.001	(0.012)	0.021*	(0.012)
Entr. exp. (s.)	0.020**	(0.008)	0.007	(0.011)	0.027**	(0.011)
Human Capital - highest educational degree$^{(1)}$						
Without	-0.036*	(0.018)	0.046	(0.101)	-0.053**	(0.022)
Master craftsman	-0.022	(0.015)	0.016	(0.024)	-0.034*	(0.019)
University degree	0.107***	(0.024)	0.047*	(0.027)	0.142***	(0.029)
Ph.D.	0.270***	(0.051)	0.102**	(0.041)	0.324***	(0.056)
R&D	0.089***	(0.016)	0.034***	(0.013)	0.117***	(0.021)
Team	0.022	(0.015)	0.054***	(0.018)	0.023	(0.019)
Het. educ. degr.	-0.040***	(0.014)	-0.042**	(0.017)	-0.048***	(0.017)
Year of foundation$^{(2)}$						
Founded in 2006	-0.001	(0.010)	-0.001	(0.011)	-0.001	(0.013)
Founded in 2007	-0.009	(0.009)	-0.006	(0.013)	-0.012	(0.013)
Industry$^{(3)}$						
HT manuf.	0.093***	(0.026)	0.040	(0.054)	0.120***	(0.031)
Tech.-int. serv.	0.148***	(0.029)	0.057	(0.046)	0.190***	(0.031)
Software	0.175***	(0.044)	0.068	(0.060)	0.220***	(0.047)
Knowl.-int. serv.	0.168***	(0.046)	0.033	(0.056)	0.223***	(0.047)
Low-tech manuf.	0.013	(0.021)	-0.022	(0.035)	0.022	(0.026)
Busin.-rel. serv.	0.093**	(0.038)	0.056	(0.047)	0.115**	(0.047)
Cons.-rel. serv.	-0.027	(0.017)	0.001	(0.051)	-0.039*	(0.021)
Construction	0.010	(0.021)	0.003	(0.046)	0.014	(0.028)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.11: Marginal effects of the double-hurdle model (share of low-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y \mid y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$Log(\frac{H}{M})$	0.190	(0.158)	0.028	(0.071)	0.259	(0.204)
$Log(\frac{L}{M})$	0.159*	(0.093)	0.059	(0.054)	0.196	(0.126)
$Log(L_{2007})$	0.016	(0.021)	-0.329***	(0.045)	0.220***	(0.017)
$Log(K)$	-0.008**	(0.003)	-0.003	(0.002)	-0.010**	(0.004)
Human Capital - professional experience						
Log(industry exp.)	-0.017***	(0.004)	-0.007	(0.004)	-0.021***	(0.006)
Entr. exp. (n. s.)	-0.013	(0.017)	-0.014	(0.013)	-0.012	(0.019)
Entr. exp. (s.)	-0.030	(0.021)	-0.001	(0.009)	-0.037	(0.025)
Human Capital - highest educational degree$^{(1)}$						
Without	0.154***	(0.043)	0.024*	(0.012)	0.182***	(0.051)
Master craftsman	-0.092***	(0.022)	-0.017*	(0.009)	-0.111***	(0.026)
University degree	-0.127***	(0.017)	-0.023***	(0.006)	-0.154***	(0.021)
Ph.D.	-0.160***	(0.022)	-0.064***	(0.019)	-0.194***	(0.028)
R&D	-0.038**	(0.017)	-0.002	(0.010)	-0.047**	(0.020)
Team	-0.036*	(0.020)	0.038***	(0.013)	-0.060***	(0.023)
Het. educ. degr.	0.065**	(0.026)	0.044**	(0.021)	0.062**	(0.028)
Year of foundation$^{(2)}$						
Founded in 2006	0.008	(0.016)	0.010	(0.007)	0.006	(0.019)
Founded in 2007	-0.031*	(0.017)	0.004	(0.008)	-0.041**	(0.021)
Industry$^{(3)}$						
HT manuf.	-0.115***	(0.025)	-0.045***	(0.011)	-0.134***	(0.032)
Tech.-int. serv.	-0.083***	(0.028)	-0.016*	(0.010)	-0.101***	(0.037)
Software	-0.072**	(0.033)	-0.039***	(0.012)	-0.080*	(0.043)
Knowl.-int serv.	-0.118***	(0.044)	0.002	(0.009)	-0.151***	(0.055)
Low-tech manuf.	-0.036	(0.039)	-0.003	(0.014)	-0.045	(0.048)
Busin.-rel. serv.	0.042	(0.048)	0.018	(0.014)	0.046	(0.058)
Cons.-rel. serv.	0.066	(0.053)	0.034***	(0.010)	0.069	(0.065)
Construction	-0.109***	(0.026)	-0.035***	(0.008)	-0.130***	(0.035)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

However, no significant effect can be observed on the conditional or unconditional mean of the share of high-skilled workers. Furthermore, the effect on the probability to employ high-skilled workers is rather small in size.

For the share of low-skilled employees, I find a negative effect of the capital stock on the probability to employ low-skilled workers and on the unconditional mean of the share of low-skilled workers in both the hurdle and the double-hurdle model. The size of the effect does not differ much between the hurdle and the double-hurdle model. As for high-skilled worker, the effect is rather small in size. Putting these effects together, there seems to be a indication of capital-skill complementarity in young firms. However, the capital-skill complementarity seems to be not that important in determining the skill-structure of jobs created by new firms.

Specific human capital has a significant influence on the employment structure within a newly established firm. The probability to employ high-skilled workers is larger for founders with longer industry experience. On the other hand, the probability to employ low-skilled workers becomes smaller as industry experience increases. Likewise, the unconditional mean of the share of high-skilled (low-skilled) workers is larger (smaller) the more industry experience a firm's founders have accumulated. But it turns out that the effect is very small in size.

Entrepreneurial experience is only found to to have an influence on the demand for high-skilled employees and not on the demand for low-skilled employees. If a founder was successful as an entrepreneur, i.e. his previous business still exists, the probability to employ high-skilled workers increases by 3 percentage points. Likewise, the unconditional share of high-skilled workers increases by about two percentage points. The size of the effect is very similar regardless the model used. Even if a founder has entrepreneurial experience which was not successful, i.e. the previous business has been either closed voluntary or become insolvent, the hurdle model predicts a higher share of high-skilled workers compared to founders who do not have any entrepreneurial experience. However, the positive effect of unsuccessful entrepreneurial experience on the skill-structure of new firms' employees is not robust when using the double-hurdle model.

The structure of jobs created in new firms is largely determined by the generic human capital as measured by the educational degree of the founders. As described in section 5.4.2, I can distinguish five different categories of formal education. Vocational training serves as point of reference, i.e. all effects are calculated as compared to firms which are established by founders with vocational training. Compared to firms founded by persons who completed vocational training, firms founded by persons without any professional training employ a smaller fraction of high-skilled workers. This effect is driven by their significantly lower probability of employing high-skilled workers (-7 percentage points). On the other hand, founders who have not completed any professional training have a significant higher demand for low-skilled workers. The probability to employ low-skilled workers is about 19 percentage points higher for founders without any professional training (as compared to founders with vocational training). Since the positive effect on the share of low-skilled workers (16 percentage points) is so much higher than the negative effect on the share of high-skilled workers (-5 percentage points), a missing professional education negatively affects the demand not only for high-skilled but also for medium-skilled workers.

Also, firms founded by persons who completed professional school (*master craftsman*) are found to demand a lower share of high-skilled workers. But, unlike the badly educated founders, they also employ a lower fraction of low-skilled workers. This means that founders with a master craftsman diploma rely, as compared to founders with vocational training, much more on the work of medium-skilled workers.

A university degree raises the probability of employing high-skilled workers by about 14 percentage points. Given these founders employ high-skilled workers, they also employ a significantly larger share of high-skilled workers in case of the double-hurdle model.[6] All in all, the share of high-skilled workers is about 10 percentage points higher in start-ups of founders with a university degree. The effect is even larger if the founders have completed postgraduate studies. Compared to founders with vocational training their unconditional share of high-skilled workers is about 26 percentage points higher. On the other hand, founders with completed university studies have a lower probability of employing low-skilled workers. They also employ a smaller share of low-skilled workers than founders with vocational training given they employ at least one low-skilled person. The same effect is found for founders who completed postdoctoral studies (*Ph.D.*) and for founders who completed professional school (*master craftsman*). For founders who have completed a postdoctoral degree, the effect is almost double the effect of master craftsmen (see Tables 5.9 and 5.11). Since shares add up to one, the effect of a university degree or a postgraduate degree on the demand for medium-skilled workers can be approximated by comparing the direction and size of the effect on the

[6]The conditional effect is insignificant in the hurdle model.

low-skilled and high-skilled workers. Since the effect of a university degree on the share of high-skilled workers and the effect of a university degree on the share of low-skilled workers are opposite in direction but approximately of equal size, having a university degree seems to have no influence on the share of medium skilled workers. This is not true in case of postgraduate studies. The effect of having completed postgraduate studies on the share of high-skilled workers (26 percentage points) in absolute values is much larger than the effect of postgraduate studies on the share of low-skilled workers (-16 percentage points). Consequently, firms founded by persons who completed their doctoral studies employ also a smaller fraction of medium-skilled workers.

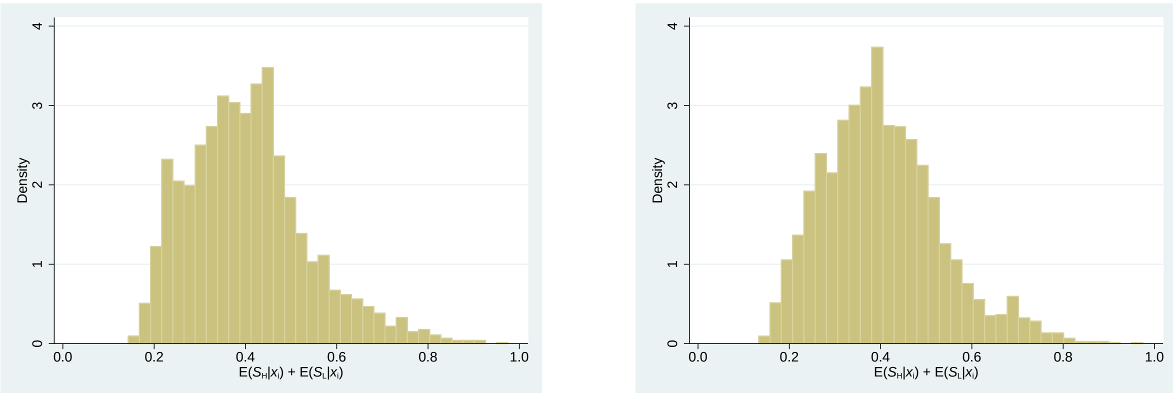
The hypothesis of a skill-biased technical change is fully supported for newly established firms. If a firm conducts R&D continuously, both the probability of employing high-skilled workers and the conditional share of high-skilled employees are positively affected. The probability to employ high-skilled workers increases by about 13 percentage points, the conditional share of high-skilled workers increases by 3 percentage points, and the unconditional share of high-skilled workers increases by 10 percentage points.

Furthermore, the probability of employing low-skilled workers is significantly lower in firms with continuous R&D (-6 percentage points). Accordingly, the unconditional share of low-skilled workers is smaller (-4 percentage points) in firms which conduct R&D continuously. When comparing the direction and the size of these two effects, not only low-skilled workers but also medium-skilled workers suffer from ongoing technological change. This result is in line with the results of Jacobebbinghaus and Zwick (2002) who investigated mature firms and find that technological change not only reduces relative demand for low-skilled workers but also reduces relative demand for medium-skilled workers.

Let us now have a short look at the control variables. The team dummy has a positive influence on the conditional share of high-skilled workers. The probability of employing low-skilled workers is negatively related to the team dummy. However, there is a positive relationship of founding within a team of founders and the conditional share of low-skilled workers. The overall effect on the unconditional share of low-skilled workers is negative. Interestingly, if there is heterogeneity in the educational degrees of the founders within the team, demand for high-skilled workers is negatively affected. Both the probability of employing high-skilled workers and the conditional and unconditional share of high-skilled workers is lower if the firm is founded by persons who hold different educational degrees. On the other hand, relative demand for low-skilled workers is positively affected by the heterogeneity of educational degrees within the team of founders.

Firm age is not found to have an influence on the share of high-skilled workers. However, in the first year of their operations firms employ a smaller fraction of low-skilled workers.

Not surprisingly, the structure of jobs differs largely between industries. Retail and wholesale firms serve as reference category. Firms operating in research- and knowledge-intensive industries, such as high-tech manufacturing, technology-intensive services, software, and knowledge-intensive services, employ a significantly larger share of high-skilled workers and a significantly smaller share of low-skilled workers. Consumer-related services employ less high-skilled workers than retail and wholesale firms. Relative demand for high-skilled workers is found to be significantly higher in business-related services as compared to retail and wholesale. Since the share of low-skilled workers is significantly lower in construction, these firm rely more on medium-skilled workers than retail and wholesale firms.



(a) Hurdle model (b) Double-hurdle model

Figure 5.1: Sum of predicted shares ($\hat{S}_H + \hat{S}_L$) for the hurdle model and the double-hurdle model

Note: Observations with $\hat{S}_H + \hat{S}_L > 1$ are excluded.
Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Comparing the hurdle and the double-hurdle model (Table 5.8 vs. Table 5.10 and Table 5.9 vs. 5.11), the results turn out to be rather robust with respect to the corner solution model chosen. When comparing the sum of predicted shares ($\hat{S}_H + \hat{S}_L$), the double-hurdle model performs slightly better than the hurdle model. In the double-hurdle model, only one observation is predicted to employ more than 100 percent high- and low-skilled workers. But the sum of predictions exceeds 100 percent for 14 observations in the hurdle model. Figure 5.1 displays two histograms of the sum of predicted shares of the hurdle and double-hurdle model, respectively.

5.5 Conclusions

Skills and productive knowledge embodied in a person, commonly known as human capital, has been widely acknowledged in economics to be an important factor of production. In entrepreneurship research, the human capital of the founders has been found to be a major predictor of young firms' survival and firm performance. Furthermore, labor demand is largely influenced by entrepreneurs' human capital when labor is treated as homogeneous.

In this chapter, I have investigated the effect of the specific and generic human capital of a firm's founders on heterogeneous labor demand of young firms. It turns out that the educational degree of the founders considerably determines the qualification structure of the workforce in young firms. The results suggest that both a high level of specific human capital and a high level of generic human capital are related to skill upgrading in young firms. Moreover, I find evidence that a skill-biased technical change is relevant even for very young firms. Skills and physical capital prove to be complements. However, this effect is rather small. Most of the effects turn out to be robust in all corner solution outcome models estimated. The study contributes to the literature by investigating heterogeneous labor demand of newly established firms and by introducing the concept of the importance of human capital into a framework of heterogeneous labor demand.

Two major issues when investigating heterogeneous labor demand, organizational change and internationalization, could not be addressed in this study. While organizational change is less relevant for young firms, further research might address the question of heterogeneous labor demand of "born globals".

5.A Appendix

5.A1 Double-hurdle model

The d1-ml procedure in Stata makes use of analytical derivatives of the log-likelihood function. The first derivatives are given as follows:

$$
\begin{aligned}
\frac{\partial logL}{\partial \gamma} &= \sum_0 -\frac{\phi_1 \Phi_2}{1-\Phi_1\Phi_2}\boldsymbol{z}_i + \sum_+ \frac{\phi_1}{\Phi_1}\boldsymbol{z}_i \\
\frac{\partial logL}{\partial \boldsymbol{\beta}} &= \sum_0 -\frac{1}{\sigma_i}\frac{\phi_2 \Phi_1}{1-\Phi_1\Phi_2}\boldsymbol{x}_i + \sum_+ \frac{1}{\sigma_i}\frac{y_i-\boldsymbol{x}_i'\beta}{\sigma_i}\boldsymbol{x}_i \\
\frac{\partial logL}{\partial \boldsymbol{\alpha}} &= \sum_0 \frac{\phi_2 \Phi_1}{1-\Phi_1\Phi_2}\cdot\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i}\boldsymbol{w}_i + \sum_+ \left[\left(\frac{y_i-\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i}\right)^2 - 1\right]\boldsymbol{w}_i,
\end{aligned}
$$

with $\phi_1 = \phi(\boldsymbol{z}_i'\boldsymbol{\gamma})$, $\phi_2 = \phi(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i})$, $\Phi_1 = \Phi(\boldsymbol{z}_i'\boldsymbol{\gamma})$, $\Phi_2 = \Phi(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i})$ and $\sigma_i = \sigma \cdot \exp(\boldsymbol{w}_i'\boldsymbol{\alpha})$.

Stata programming code double-hurdle regression (Cragg model)

```
program define hetcragg_ll
version 6
args todo b lnf g negH g1 g2 g3
tempvar x1b x2b sigma d p z w p0 p1 lnfj s

mleval ‘x1b’                = ‘b’, eq(1)
mleval ‘x2b’                = ‘b’, eq(2)
mleval ‘sigma’                = ‘b’, eq(3)

quietly {
        gen double      ‘d’ = ($ML_y1 > 0 & $ML_y1 < .)
        gen double      ‘p’ =  normprob(‘x1b’)
        gen double      ‘s’ = exp(‘sigma’)
        gen double      ‘z’ = (‘x2b’)/(‘s’)
        gen double      ‘w’ = ($ML_y1-‘x2b’)/(‘s’)
        gen double      ‘p0’= 1-(‘p’*normprob(‘z’))
        gen double      ‘p1’= ‘p’*normd(‘w’)/‘s’
        gen double      ‘lnfj’= ln(‘p0’) if ‘d’==0
```

```
        replace         ‘lnfj’= ln(‘p1’)  if ‘d’==1
        mlsum           ‘lnf’ = ‘lnfj’
}
if ‘todo’==0 | ‘lnf’==. {exit}

quietly replace ///
‘g1’ = -(normd(‘x1b’)*normprob(‘z’))/(1-‘p’*normprob(‘z’)) if ‘d’==0
quietly replace                 ‘g1’ = normd(‘x1b’)/‘p’   if ‘d’==1

quietly replace ///
‘g2’ = - (1/‘s’)*((normd(‘z’)*‘p’)/(1-‘p’*normprob(‘z’))) if ‘d’==0
quietly replace                 ‘g2’ = (1/‘s’)*‘w’        if ‘d’==1

quietly replace ///
‘g3’ = (normd(‘z’)*‘p’/(1-‘p’*normprob(‘z’)))*(‘z’) if ‘d’==0
quietly replace                 ‘g3’ = ((‘w’)^2-1)        if ‘d’==1

tempname d1 d2 d3
mlvecsum ‘lnf’ ‘d1’ = ‘g1’, eq(1)
mlvecsum ‘lnf’ ‘d2’ = ‘g2’, eq(2)
mlvecsum ‘lnf’ ‘d3’ = ‘g3’, eq(3)

matrix ‘g’ = (‘d1’, ‘d2’, ‘d3’)
end

ml model d1 hetcragg_ll (Hurdle1: $lhs= $rhs1) ///
(Hurdle2: $rhs2)(sigma:$het), cluster($clust)
ml search
ml max
```

5.A2 The Box-Cox double-hurdle model

The Box-Cox hurdle model was first presented by Jones and Yen (2000) and is based on Cragg's (1971) double-hurdle model with the dependent variable transformed. Hence, compared to the double-hurdle model one more parameter, the transformation parameter λ has to be estimated. The transformation relaxes the normality assumption of unobserved errors on which the standard double-hurdle model is built. Similarly to Cragg's double-hurdle model the model is specified by two latent variables.

$$d_i^* \;=\; \boldsymbol{z}_i^{'}\boldsymbol{\gamma} + \epsilon_i, \qquad \epsilon_i \sim \mathcal{N}(0,1), \quad i = 1, 2, \ldots, n,$$

$$y_i^* \quad = \quad \boldsymbol{x}_i'\boldsymbol{\beta} + u_i, \qquad u_i \sim \mathcal{N}(0, \sigma^2), \quad i = 1, 2, \ldots, n,$$

where u_i and ϵ_i are independently distributed.

The observed dependent variable is transformed as follows:

$$y_i^T \quad = \quad \begin{cases} \frac{y_i^\lambda - 1}{\lambda} & \text{if} \quad \lambda \neq 0, \\ ln(y_i) & \text{if} \quad \lambda = 0. \end{cases}$$

The Box-Cox double-hurdle model is then given by

$$y_i^T \quad = \quad \begin{cases} y_i^* & \text{if} \quad y_i^* > \frac{1}{\lambda} \quad \text{and} \quad d_i^* > 0 \\ 0 & \text{if} \quad y_i^* \leq \frac{1}{\lambda} \quad \text{or} \quad d_i^* \leq 0, \end{cases}$$

and the log-likelihood of the Box-Cox double-hurdle model is

$$\begin{aligned} \text{Log}L \quad &= \quad \sum_0 ln \left[1 - \Phi\left(\boldsymbol{z}_i'\boldsymbol{\gamma}\right) \Phi\left(\frac{\frac{1}{\lambda} + \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i} \right) \right] \\ &+ \quad \sum_+ ln \left[\Phi\left(\boldsymbol{z}_i'\boldsymbol{\gamma}\right) y_i^{\lambda - 1} \frac{1}{\sigma_i} \phi\left(\frac{y_i^T - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i} \right) \right]. \end{aligned}$$

The first order derivatives are derived analytically:

$$\begin{aligned} \frac{\partial \text{Log}L}{\partial \boldsymbol{\gamma}} \quad &= \quad \sum_0 -\frac{\phi_1 \Phi_2}{1 - \Phi_1 \Phi_2} \boldsymbol{z}_i + \sum_+ \frac{\phi_1}{\Phi_1} \boldsymbol{z}_i, \\ \frac{\partial \text{Log}L}{\partial \boldsymbol{\beta}} \quad &= \quad \sum_0 -\frac{1}{\sigma_i} \frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \boldsymbol{x}_i + \sum_+ \frac{1}{\sigma_i} \frac{y_i^T - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i} \boldsymbol{x}_i, \\ \frac{\partial \text{Log}L}{\partial \boldsymbol{\alpha}} \quad &= \quad \sum_0 \left[\frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \frac{\frac{1}{\lambda} + \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i} \right] \boldsymbol{w}_i + \sum_+ \left[\left(\frac{y_i^T - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i} \right)^2 - 1 \right] \boldsymbol{w}_i, \\ \frac{\partial \text{Log}L}{\partial \lambda} \quad &= \quad \sum_0 \frac{1}{\sigma_i \lambda^2} \frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \\ &+ \quad \sum_+ \left[-\left(\frac{y_i^\lambda [\lambda ln(y_i) - 1] + 1}{\sigma_i \lambda^2} \right) \left(\frac{y_i^T - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i} \right) + ln(y_i) \right], \end{aligned}$$

with $\phi_1 = \phi(\boldsymbol{z}_i'\boldsymbol{\gamma})$, $\phi_2 = \phi(\frac{\frac{1}{\lambda} + \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i})$, $\Phi_1 = \Phi(\boldsymbol{z}_i'\boldsymbol{\gamma})$, $\Phi_2 = \Phi(\frac{\frac{1}{\lambda} + \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_i})$ and $\sigma_i = \sigma \cdot \exp(\boldsymbol{w}_i'\boldsymbol{\alpha})$.

Stata programming code Box-Cox double-hurdle regression

```
program define hetbcdh
version 6
args todo b lnf g negH g1 g2 g3 g4
tempname l l2
tempvar x1b x2b sigma d p z w s p0 p1 yt lnfj

mleval ‘x1b’    =‘b’, eq(1)
mleval ‘x2b’    =‘b’, eq(2)
mleval ‘sigma’  =‘b’, eq(3)
mleval ‘l’      =‘b’, eq(4) scalar

quietly {
        gen double  ‘d’     = ($ML_y1 >0 & $ML_y1 <.)
        gen double  ‘p’     = normprob(‘x1b’)
        gen double  ‘s’     = exp(‘sigma’)
        gen double  ‘l2’    = ‘l’
        gen double  ‘yt’    = ($ML_y1^(‘l2’)-1)/‘l2’
        gen double  ‘z’     = (‘x2b’ + (1/‘l2’))/(‘s’)
        gen double  ‘w’     = (-‘x2b’ + ‘yt’)/(‘s’)
        gen double  ‘p0’    = 1-(‘p’*normprob(‘z’))
        gen double  ‘p1’    = ($ML_y1^(‘l2’-1))*‘p’*normd(‘w’)/‘s’
        gen double  ‘lnfj’  = ln(‘p0’) if ‘d’==0
        replace     ‘lnfj’  = ln(‘p1’)  if ‘d’==1
        mlsum       ‘lnf’   = ‘lnfj’
}

if ‘todo’==0 | ‘lnf’==. {exit}

quietly replace ///
‘g1’ = -(normd(‘x1b’)*normprob(‘z’))/(1-‘p’*normprob(‘z’)) if ‘d’==0
quietly replace         ‘g1’ = normd(‘x1b’)/‘p’ if ‘d’==1

quietly replace ///
‘g2’ = - (1/‘s’)*((normd(‘z’)*‘p’)/(1-‘p’*normprob(‘z’))) if ‘d’==0
quietly replace         ‘g2’ = (1/‘s’)*‘w’ if ‘d’==1

quietly replace ///
‘g3’ = (normd(‘z’)*‘p’/(1-‘p’*normprob(‘z’)))*(‘z’) if ‘d’==0
quietly replace         ‘g3’ = ((‘w’)^2-1) if ‘d’==1
```

```
quietly replace ///
`g4' = (1/(`s'*`l2'^2))*((normd(`z')*`p')/(1-`p'*normprob(`z'))) if `d'==0
quietly replace         `g4' = ///
log($ML_y1)-((($ML_y1^`l2')*(`l2'*log($ML_y1)-1)+1)/(`s'*`l2'^2))*(`w') if `d'==1


tempname d1 d2 d3 d4
mlvecsum `lnf' `d1' = `g1', eq(1)
mlvecsum `lnf' `d2' = `g2', eq(2)
mlvecsum `lnf' `d3' = `g3', eq(3)
mlvecsum `lnf' `d4' = `g4', eq(4)


matrix `g' = (`d1', `d2', `d3', `d4')

end

ml model d1 hetbcdh (Hurdle1: $lhs= $rhs1) ///
(Hurdle2: $rhs2)(sigma: $het)(lambda:), cluster($clust)
ml search
ml max
```

5.A3 Additional regression tables

Table 5.12: Hurdle models of heterogeneous labor demand (high-skilled employees)

	(1) First stage Probit		Share of high-skilled employees (2a) Second stage Truncated normal		(2b) Second stage Log-linear		(2c) Second stage Box-Cox	
	coeff.	se	coeff.	se	coeff.	se	coef	se
$Log(\frac{H}{M})$	-0.785*	(0.427)	0.195	(0.196)	0.278	(0.200)	0.257	(0.165)
$Log(\frac{L}{M})$	-0.578*	(0.347)	-0.127	(0.139)	-0.230	(0.184)	-0.180	(0.143)
$Log(L_{2007})$	0.358***	(0.068)	-0.335***	(0.090)	-0.507***	(0.080)	-0.293***	(0.093)
$Log(K)$	0.022*	(0.012)	-0.005	(0.004)	-0.005	(0.005)	-0.005	(0.004)
Miss $log(K)$	0.180	(0.176)	-0.051	(0.048)	-0.069	(0.063)	-0.061	(0.055)
Human Capital - professional experience								
Log(industry exp.)	0.059**	(0.025)	-0.008	(0.015)	-0.009	(0.022)	-0.007	(0.015)
Entr. exp. (n. s.)	0.120*	(0.063)	0.005	(0.025)	0.024	(0.033)	0.008	(0.029)
Entr. exp. (s.)	0.151***	(0.056)	0.007	(0.027)	0.022	(0.034)	0.011	(0.028)
Human Capital - highest educational degree(1)								
Without	-0.438*	(0.226)	0.073	(0.185)	0.112	(0.287)	0.128	(0.163)
Master craftsman	-0.246**	(0.113)	0.045	(0.056)	0.076	(0.079)	0.044	(0.063)
University degree	0.646***	(0.102)	0.097	(0.062)	0.146*	(0.083)	0.128**	(0.060)
Ph.D.	1.002***	(0.147)	0.167**	(0.066)	0.233***	(0.088)	0.199***	(0.063)
R&D	0.543***	(0.079)	0.059**	(0.023)	0.084**	(0.035)	0.071**	(0.030)
Team	0.092	(0.092)	0.141***	(0.054)	0.207***	(0.065)	0.120**	(0.055)
Het. educ. degr.	-0.239*	(0.127)	-0.100**	(0.045)	-0.135*	(0.076)	-0.110**	(0.055)
Foundation year(2)								
Founded 2006	-0.006	(0.073)	-0.000	(0.026)	0.004	(0.036)	0.002	(0.029)
Founded 2007	-0.054	(0.082)	-0.026	(0.033)	-0.044	(0.035)	-0.037	(0.029)
Industry(3)								
HT manuf.	0.526***	(0.126)	0.053	(0.082)	0.060	(0.130)	0.076	(0.102)
Techn.-int. serv.	0.728***	(0.106)	0.077	(0.078)	0.110	(0.116)	0.120	(0.093)
Software	0.716***	(0.135)	0.127	(0.092)	0.159	(0.126)	0.170*	(0.101)
Knowl.-int. serv.	0.881***	(0.125)	0.041	(0.092)	0.058	(0.131)	0.060	(0.104)
Low-tech manuf.	0.158	(0.110)	-0.070	(0.079)	-0.137	(0.122)	-0.053	(0.095)
Business-rel. serv.	0.341**	(0.162)	0.090	(0.082)	0.130	(0.117)	0.142	(0.094)
Cons.-rel. serv.	-0.255*	(0.152)	0.006	(0.103)	-0.044	(0.161)	0.008	(0.113)
Construction	0.063	(0.172)	0.004	(0.072)	-0.025	(0.125)	0.013	(0.094)
Constant	-2.460***	(0.291)	0.922***	(0.254)	-0.135	(0.249)	-0.270	(0.192)
σ_i								
Wald test on joint sign. of var. in $\mathbf{w_i}$ ($\chi^2(11)$)			68.04***	[0.000]	410.85***	[0.000]	111.69***	[0.000]
$Log(\sigma)$			-2.163***	(0.372)	-1.843***	(0.175)	-1.721***	(0.166)
λ							0.629***	(0.221)
ll			-1037		-1086		-1056	
Observations			2988		2988		2988	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.13: Hurdle models of heterogeneous labor demand (low-skilled employees)

	Share of low-skilled employees							
	(1) First stage Probit		(2a) Second stage Truncated normal		(2b) Second stage Log-linear		(2c) Second stage Box-Cox	
	coeff.	se	coeff.	se	coeff.	se	coef	se
$Log(\frac{H}{M})$	0.762	(0.501)	0.000	(0.073)	0.033	(0.092)	0.034	(0.082)
$Log(\frac{L}{M})$	0.542*	(0.318)	0.043	(0.052)	0.090	(0.073)	0.059	(0.066)
$Log(L_{2007})$	0.373***	(0.041)	-0.413***	(0.051)	-0.546***	(0.065)	-0.284***	(0.069)
$Log(K)$	-0.022**	(0.010)	-0.002	(0.002)	-0.003	(0.002)	-0.004**	(0.002)
Miss $log(K)$	-0.347***	(0.113)	-0.027	(0.022)	-0.046	(0.034)	-0.048*	(0.026)
Human Capital - professional experience								
Log(industry exp.)	-0.057***	(0.015)	-0.005	(0.004)	-0.008	(0.006)	-0.008*	(0.004)
Entr. exp. (n. s.)	0.040	(0.063)	-0.031	(0.027)	-0.042	(0.040)	-0.031	(0.030)
Entr. exp. (s.)	-0.098	(0.063)	-0.007	(0.018)	-0.003	(0.027)	-0.004	(0.019)
Human Capital - highest educational degree(1)								
Without	0.477***	(0.151)	0.046**	(0.021)	0.058*	(0.031)	0.039	(0.025)
Master craftsman	-0.285***	(0.079)	-0.037*	(0.020)	-0.051*	(0.029)	-0.048**	(0.024)
University degree	-0.392***	(0.071)	-0.051***	(0.016)	-0.075***	(0.025)	-0.065***	(0.019)
Ph.D.	-0.562***	(0.142)	-0.125***	(0.047)	-0.235**	(0.105)	-0.151***	(0.059)
R&D	-0.155**	(0.062)	-0.002	(0.021)	-0.004	(0.028)	0.000	(0.020)
Team	-0.269***	(0.066)	0.095***	(0.027)	0.136***	(0.037)	0.062**	(0.026)
Het. educ. degr.	0.136	(0.087)	0.081**	(0.037)	0.095*	(0.054)	0.063*	(0.037)
Year of foundation(2)								
Founded 2006	-0.028	(0.052)	0.027	(0.018)	0.038	(0.025)	0.033*	(0.019)
Founded 2007	-0.134**	(0.057)	0.003	(0.018)	0.006	(0.023)	0.011	(0.018)
Industry(3)								
HT manuf.	-0.266*	(0.139)	-0.108***	(0.035)	-0.159***	(0.051)	-0.132***	(0.041)
Techn.-int. serv.	-0.288**	(0.134)	-0.039**	(0.020)	-0.050*	(0.027)	-0.051**	(0.022)
Software	-0.118	(0.160)	-0.077***	(0.024)	-0.114***	(0.036)	-0.102***	(0.031)
Knowl.-int. serv.	-0.546**	(0.217)	-0.009	(0.024)	-0.022	(0.037)	-0.014	(0.028)
Low-tech manuf.	-0.144	(0.136)	0.005	(0.032)	-0.003	(0.045)	-0.004	(0.034)
Bus.-rel. serv.	0.137	(0.169)	-0.011	(0.036)	-0.006	(0.048)	0.005	(0.037)
Cons.-rel. serv.	0.170	(0.181)	0.039*	(0.021)	0.061**	(0.030)	0.047**	(0.024)
Construction	-0.282*	(0.146)	-0.081***	(0.018)	-0.119***	(0.023)	-0.105***	(0.019)
Constant	-0.227	(0.337)	1.366***	(0.075)	0.461***	(0.097)	0.246**	(0.096)
σ_i								
Wald test on joint sign. of var. in $\mathbf{w_i}$ ($\chi^2(11)$)			203.32***	[0.000]	133.94***	[0.000]	42.85***	[0.000]
$Log(\sigma)$			-2.486***	(0.118)	-2.226***	(0.139)	-2.178***	(0.150)
λ							0.893***	(0.217)
ll			-1732		-1920		-1828	
Observations			2988		2988		2988	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.
Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.14: Tobit models of heterogeneous labor demand

	Share of high-skilled employees			
	Tobit		P-Tobit	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	-0.450	(0.312)	-0.010	(0.728)
$Log(\frac{L}{M})$	-0.461*	(0.279)	-0.387	(0.294)
$Log(L_{2007})$	0.292***	(0.038)	0.042	(0.340)
$Log(K)$	0.013	(0.009)	-0.002	(0.015)
Miss $log(K)$	0.114	(0.126)	-0.056	(0.187)
Human Capital - professional experience				
Log(industry exp.)	0.041***	(0.016)	0.040**	(0.017)
Entr. exp. (n. s.)	0.081*	(0.049)	0.089	(0.069)
Entr. exp. (s.)	0.101**	(0.041)	0.094	(0.068)
Human Capital - highest educational degree$^{(1)}$				
Without	-0.252	(0.185)	0.078	(0.816)
Master craftsman	-0.189**	(0.086)	-0.164*	(0.093)
University degree	0.542***	(0.076)	0.540***	(0.116)
Ph.D.	0.737***	(0.091)	0.634*	(0.331)
R&D	0.360***	(0.062)	0.219	(0.259)
Log(team size)	0.101	(0.067)	0.052	(0.121)
Het. educ. degr.	-0.230***	(0.079)	-0.169	(0.171)
Year of foundation$^{(2)}$				
Founded 2006	0.100**	(0.051)	0.119***	(0.042)
Founded 2007	-0.046	(0.065)	0.011	(0.040)
Industry$^{(3)}$				
HT manuf.	0.378**	(0.187)	0.640	(0.576)
Techn.-int. serv.	0.576***	(0.180)	0.826	(0.512)
Software	0.559***	(0.207)	0.880**	(0.397)
Knowl.-int. serv.	0.601***	(0.182)	0.826	(0.509)
Low-tech manuf.	-0.067	(0.208)	0.330	(0.559)
Busin.-rel. serv.	-0.374	(0.269)	0.254	(0.642)
Cons.-rel. serv.	-0.361	(0.270)	-0.141	(0.348)
Construction	0.100	(0.206)	0.187	(0.288)
Constant	-1.978***	(0.287)	-1.245**	(0.598)
σ_i				
Test on joint sign. of var. in $\mathbf{w_i}$ ($\chi^2(11)$)	100.94***	[0.000]	368.01***	[0.000]
$Log(\sigma)$	0.126	(0.125)	0.058	(0.171)
p			0.502	(0.333)
ll	-1291		-1275	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale. 2988 Observations.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.14 – Continued

	Share of low-skilled employees			
	Tobit		P-Tobit	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	0.467*	(0.283)	0.037	(0.076)
$Log(\frac{L}{M})$	0.310	(0.218)	0.062	(0.061)
$Log(L_{2007})$	0.222***	(0.025)	-0.299***	(0.041)
$Log(K)$	-0.010	(0.006)	-0.003*	(0.002)
Miss $log(K)$	-0.181**	(0.075)	-0.042*	(0.024)
Human Capital - professional experience				
Log(industry exp.)	-0.046***	(0.006)	-0.007*	(0.004)
Entr. exp. (n. s.)	0.061	(0.043)	-0.029	(0.028)
Entr. exp. (s.)	-0.055	(0.036)	-0.004	(0.019)
Human Capital - highest educational degree$^{(1)}$				
Without	0.329***	(0.088)	0.039*	(0.022)
Master craftsman	-0.203***	(0.054)	-0.044*	(0.023)
University degree	-0.292***	(0.048)	-0.065***	(0.017)
Ph.D.	-0.425***	(0.093)	-0.166***	(0.060)
R&D	-0.076**	(0.039)	-0.007	(0.020)
Log(team size)	-0.086**	(0.035)	0.061**	(0.025)
Het. educ. degr.	0.135**	(0.053)	0.074**	(0.035)
Year of foundation$^{(2)}$				
Founded 2006	-0.018	(0.040)	0.033*	(0.019)
Founded 2007	-0.026	(0.042)	0.009	(0.017)
Industry$^{(3)}$				
HT manuf.	-0.218**	(0.104)	-0.132***	(0.040)
Techn.-int. serv.	-0.369***	(0.110)	-0.049**	(0.022)
Software	-0.187*	(0.111)	-0.095***	(0.030)
Knowl.-int. serv.	-0.486***	(0.162)	-0.019	(0.029)
Low-tech manuf.	-0.094	(0.113)	-0.002	(0.034)
Busin.-rel. serv.	0.036	(0.116)	0.004	(0.035)
Cons.-rel. serv.	0.200*	(0.113)	0.047**	(0.021)
Construction	-0.216	(0.132)	-0.099***	(0.019)
Constant	-0.152	(0.215)	1.258***	(0.071)
σ_i				
Test on joint sign. of var. in $\mathbf{w_i}$ ($\chi^2(11)$)	277.25***	[0.000]	52.80***	[0.000]
$Log(\sigma)$	0.240***	(0.082)	-2.292***	(0.155)
p			0.402***	(0.026)
ll	-2333		-1988	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale. 2988 Observations.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.15: Box-Cox double-hurdle model of heterogeneous labor demand

	Share of high-skilled employees			
	Hurdle 1		Hurdle 2	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	-0.721	(0.479)	0.173	(0.192)
$Log(\frac{L}{M})$	-0.344	(0.385)	-0.224*	(0.134)
$Log(L_{2007})$	0.689***	(0.117)	-0.264***	(0.084)
$Log(K)$	0.021*	(0.012)	-0.005	(0.004)
Miss $log(K)$	0.160	(0.186)	-0.056	(0.054)
Human Capital - professional experience				
Log(industry exp.)	0.071***	(0.027)	-0.007	(0.012)
Entr. exp. (n. s.)	0.140**	(0.068)	-0.007	(0.026)
Entr. exp. (s.)	0.137**	(0.057)	0.017	(0.024)
Human Capital - highest educational degree$^{(1)}$				
Without	-0.547**	(0.245)	0.083	(0.165)
Master craftsman	-0.291***	(0.111)	0.031	(0.051)
University degree	0.632***	(0.115)	0.109*	(0.058)
Ph.D.	1.051***	(0.167)	0.167***	(0.057)
R&D	0.510***	(0.087)	0.069***	(0.023)
Team	-0.031	(0.108)	0.106**	(0.050)
Het. educ. degr.	-0.244*	(0.133)	-0.087**	(0.039)
Year of foundation$^{(2)}$				
Founded 2006	-0.016	(0.078)	0.005	(0.027)
Founded 2007	-0.007	(0.102)	-0.046	(0.033)
Industry$^{(3)}$				
HT manuf.	0.484***	(0.162)	0.093	(0.099)
Techn.-int. serv.	0.776***	(0.135)	0.102	(0.092)
Software	0.786***	(0.155)	0.136	(0.096)
Knowl.-int. serv.	0.889***	(0.159)	0.065	(0.104)
Low-tech manuf.	0.229*	(0.130)	-0.041	(0.095)
Busin.-rel. serv.	0.517**	(0.210)	0.069	(0.094)
Cons.-rel. serv.	-0.215	(0.180)	-0.053	(0.128)
Construction	0.025	(0.205)	0.043	(0.093)
Constant	-2.828***	(0.279)	-0.210	(0.256)
σ_i				
Test on joint sign. of var. in $\mathbf{w_i}$ ($\chi^2(11)$)	49.99*** [0.000]			
$Log(\sigma)$	-1.859*** (0.376)			
λ	1.201*** (0.276)			
ll	1027			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale. 2988 Observations.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 5.15 – Continued

	Share of low-skilled employees			
	Hurdle1		Hurdle 2	
	coeff.	se	coeff.	se
$Log(\frac{H}{M})$	0.638	(0.535)	0.025	(0.065)
$Log(\frac{L}{M})$	0.508	(0.330)	0.051	(0.049)
$Log(L_{2007})$	0.713***	(0.056)	-0.300***	(0.054)
$Log(K)$	-0.027**	(0.012)	-0.002	(0.002)
Miss $log(K)$	-0.415***	(0.139)	-0.030	(0.020)
Human Capital - professional experience				
Log(industry exp.)	-0.050***	(0.015)	-0.007*	(0.004)
Entr. exp. (n. s.)	0.017	(0.072)	-0.025	(0.024)
Entr. exp. (s.)	-0.137*	(0.071)	-0.002	(0.017)
Human Capital - highest educational degree$^{(1)}$				
Without	0.483***	(0.167)	0.039**	(0.020)
Master craftsman	-0.319***	(0.081)	-0.036*	(0.019)
University degree	-0.393***	(0.078)	-0.058***	(0.016)
Ph.D.	-0.490***	(0.166)	-0.123***	(0.044)
R&D	-0.158**	(0.075)	-0.004	(0.019)
Team	-0.419***	(0.086)	0.069***	(0.025)
Het. educ. degr.	0.069	(0.095)	0.076**	(0.031)
Year of foundation$^{(2)}$				
Founded 2006	-0.069	(0.056)	0.030*	(0.016)
Founded 2007	-0.174***	(0.063)	0.009	(0.016)
Industry$^{(3)}$				
HT manuf.	-0.175	(0.157)	-0.123***	(0.037)
Techn.-int. serv.	-0.255*	(0.143)	-0.042**	(0.019)
Software	-0.082	(0.167)	-0.077***	(0.023)
Knowl.-int. serv.	-0.542**	(0.219)	-0.012	(0.021)
Low-tech manuf.	-0.131	(0.142)	-0.005	(0.031)
Busin.-rel. serv.	0.158	(0.179)	0.002	(0.030)
Cons.-rel. serv.	0.145	(0.191)	0.038**	(0.019)
Construction	-0.290*	(0.149)	-0.084***	(0.016)
Constant	-0.429	(0.348)	0.260***	(0.078)
σ_i				
Test on joint sign. of var. in $\mathbf{w_i}$ ($\chi^2(11)$)	91.59*** [0.000]			
$Log(\sigma)$	-2.462*** (0.144)			
λ	1.433*** (0.173)			
ll	-1752			

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale. 2988 Observations.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

6 Summary and general conclusion

Throughout the chapters of this thesis, I studied the importance of founders' human capital in newly established firms from different perspectives.

New firms are heterogeneous in many dimensions. They differ in initial firm size, some start-ups grow faster than others, they differ with regard to the people they employ, and their contribution to technology transfer varies largely.

The importance of human capital turns out to be a substantial part of the answer to each of the research questions addressed in the respective chapters.

1. Why are some academic spin-offs established earlier than others?

2. How does the time which elapses after leaving university and firm foundation influence the performance of academic start-ups?

3. Why do some firms start larger than others?

4. What are the factors which determine the qualification structure of employees in newly established firms?

In order to address these questions, I followed an empirical approach. After reviewing the relevant literature, I developed the hypotheses drawing upon theoretical and conceptual considerations. Using different data sets on firm foundations in Germany and applying adequate econometrical methods, the hypothesis have been tested and interesting insights have been gained.

Chapter 2 and chapter 3 focus on a specific topic of human capital in newly established firms, that is academic entrepreneurship. Academic start-ups, in particular academic spin-offs, facilitate knowledge transfer from public research. This academic knowledge, be it academic skills, newly developed methods, or research results, is one component of academic entrepreneur's human capital.

From the analysis in the second chapter, we have drawn the conclusion that academic spin-off's transfer speed is substantially accelerated if the founders combine knowledge from different sources, or if the spin-off is established within a team of founders. These are clear indications for complementarities in skills. Either a founder with a rather specialized skill profile acquires the missing skills himself, which will need time and retards firm foundation, or he looks for suitable founding team members. Interestingly, the need to acquire complementary skills before starting a firm seems to differ among the types of technology transfer. Spin-offs which commercialize research results have significantly shorter time-lags than spin-offs which aimed to transfer academic skills into a marketable product or service. However, differences in transfer speed regarding the intensity of technology transfer might also be caused by varying lengths of the respective "window of opportunity".

The importance of combining both academic knowledge and professional experience is further substantiated by the investigation in chapter 3. Given that academic knowledge and professional experience determine the success of a newly established firm in conjuncture, the influence of the time which elapses after leaving university and founding a firm on firm performance should be inverse u-shaped. In fact, I find that the growth rate of employment is highest for firms with a time-lag of 3-5 years. This is a further indication of complementarities in skills but still compatible with a certain degree of substitutability, as the theoretical considerations of chapter 3 demonstrated. The results of the quantile regression, presented in chapter 3, furthermore point out that initial size is a significant factor of future growth along most parts of the distribution of growth rates. This finding is a relevant contribution to the empirical literature on new firms' growth since the relationship between initial size and growth has mainly been investigated in the conditional mean framework.

As initial size seems to be a simple, but crucial and persistent predictor of future performance, understanding why some firms start larger than others is desirable. That brings us to the main issue of chapter 4: identifying the determinants of start-up size. Despite the well established correlation of initial size and firm growth, the empirical literature on start-up size is rather scarce, and the determinants of start-up size have not yet been investigated for Germany. While industry effects, such as the minimum efficient scale, have been a prominent point of investigation in the early literature on start-up size, more recent research has investigated the impact of founder's human capital (Mata, 1996; Cabral and Mata, 2003; Colombo et al., 2004). Following Becker (1993), entrepreneur's human capital is distinguished into generic human capital and specific human capital. Various indicators of human capital are included in the analysis (the educational degree, general and specific working experience, entrepreneurial experience and management experience). Most human capital variables, except those of industry experience and unsuccessful entrepreneurial experience, prove to have a positive influence on start-up size. Another focus of the analysis in chapter 4 are entry strategies. Entry strategies can be manifold. We captured entry strategies by the leading decision to be active in R&D and the main motive of entry. While most founders are driven by the wish to work independently and self-determined, a non-negligible fraction of founders is driven by necessity. We distinguished four different motives of entry: independency entrepreneurship, necessity entrepreneurship, opportunity entrepreneurship and spin-out entrepreneurship. Among these motives, spin-out entrepreneurs have been found to start the largest.

After investigating how many employees work in a newly established firm, chapter 5 turned towards analyzing the question who works in newly established firms. I augmented the standard model of investigating heterogeneous labor demand by incorporating the specific characteristics of young firms, which is the knowledge capital of the founder. Comparing different corner solution outcome models, hurdle models turn out to fit the data best. The results of the hurdle models reveal the overwhelming importance of a founder's educational degree in determining employees' qualification structure within his firm. The share of high-skilled employees is about 26 percentage points higher if the firm's founder has completed postgraduate education instead of having completed vocational training, the most common educational degree in Germany. The share of low-skilled employees is about 16 percentage points lower, which implies that founders with postgraduate education also employ a lower share of medium-educated employees than founders who completed vocational training. However, the higher employment share of high-skilled workers in firms of founders with university degree lowers the demand for the low-skilled and not for the medium-skilled.

What are the findings we have at this point? The overall picture which emerges from the consolidation of all four empirical investigations is the need of an economy to invest in human capital development. The rapid changes evoked within a knowledge-based economy have to be met, which is especially true for young firms. A high stock of founder's human capital makes this challenge much easier.

Human capital consists of various components, out of which academic knowledge is just one component. Relying only on the knowledge gained at the university is not sufficient for establishing a company successfully. A founder, for example, also needs market experience, commercial intuition, leadership ability, and social skills. Increasing job specialization, which is inherent in the modern, knowledge-based economy, might prevent people from transition into self-employment, and even if they do, they might not be as successful as a generalist. In order to establish and lead a company successfully, a founder has to have skills in a variety of fields.

> "Consider the founder of a new small restaurant. In addition to being a good cook, the founder must be able to obtain funds, hire workers, choose location and decor, obtain food supplies at a reasonable cost, keep books, and market the restaurant. Being a good cook is insufficient for success." (Lazear, 2004, p. 208)

That does not mean that people should not specialize. The division of labor is the basis of a well working open economy. But the existence of complementarities in skills has certain implications on how founders should manage their start-up process. Founders should be aware that they need a certain amount of professional experience. Being a lone warrior is seldomly a good choice. Some efforts should be done in order to get other people on board and establish the firm within a team of founders. Even if the founder follows a niche strategy, by forming a team, missing skills and sparse experience of a single person can be compensated.

Furthermore, to build on investments in research and development has proved to be a wise strategy for young firms in order to succeed. Throughout all analyses presented in this thesis, it turns out that firms which rely heavily on R&D start operations at a larger scale, realize higher growth rates, and employ a larger fraction of high- and medium-skilled workers.

Existing literature on the relationship between new firm foundations and employment creation has demonstrated the positive aggregate effect on employment (Fritsch, 2008). Sustainable jobs, however, can only be created by firms which survive and grow. However, chapter 5 also revealed that high-potential start-ups, i.e. start-ups in the research- and knowledge intensive industries and start-ups which are engaged in R&D, create jobs for the high- and medium-skilled, not for the low-skilled. It seems that, in the long run, new firm foundations rather amplify, and do not alleviate, the problem of unemployment among the low-skilled. Public policy makers should be aware that educational efforts have to be taken in order to raise the educational level of the low-skilled and bring them into jobs.

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