Academic Entrepreneur's Human Capital Depreciation

Kathrin Müller *

This version: August, 2009

Abstract

Human capital is known to be one of the most important predictors of a person's earnings. With regard to entrepreneurial success, founders' human capital is an important determinant of firm's employment growth as well. This paper investigates if the depreciation of a founder's academic knowledge affects a start-up's employment growth. The depreciation of academic knowledge is investigated by quantifying the effect of the time period which elapses after the founder has left university until the start-up is founded on firm's employment growth. Using quantile regressions, human capital depreciation is found to be of crucial importance for both ordinary academic start-ups and academic spin-offs, the founders of the latter suffering even more from human capital depreciation.

Keywords human capital depreciation, employment growth, academic entrepreneurship

JEL Classification: J23, J24, L25, L26

*Centre for European Economic Research (ZEW), P.O. Box 103443, 68034 Mannheim, Germany. Phone: +49 621 1235-385, Fax: +49 621 1235-170. E-mail: kathrin.mueller@zew.de

Acknowledgments: The author would like to thank Martin Biewen, Robin Douhan, Christian Rammer and the participants of the IFN Seminar in Stockholm and the ZEW Brown Bag in Mannheim for valuable comments and discussions.

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-up's founder(s). As manifold as founders' motives for starting a business, so are founders' choices for the point in time at which the company should be set up. The age of the founders highly varies and entrepreneurs bring different levels of experience and qualification into the business. Its consequences for firm performance are clear. Usually, higher human capital of a firm's founder(s) is related to better firm performance. In empirical studies founders' human capital is mostly proxied by their educational degree or professional experience, only 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 (but small in size) 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, which is usually assumed in the vast majority of the literature, but with a substantial "time-lag" (Müller, 2008). The purpose of this paper 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 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 and effects 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" for employment growth in firms, which has been tested almost exclusively in the conditional mean framework, is reexamined in the quantile regression framework. The paper is structured as follows: the next section reviews the literature on (young) firm's employment growth in detail. Section 3 develops the hypothesis about academic founders' human capital depreciation. Results of the empirical analysis are presented in section 4. Finally, the conclusions of this paper are drawn in section 5.

2 Literature review

The determining factors of new firms' employment growth analyzed by empirical studies up to now can be classified into three main groups: founder-specific factors, firm-specific factors and the external characteristics. Founders' human capital endowment is one of the most prominent founder-specific factors. Firm size, firm age, firm's innovation activities, legal form and internationalization 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.

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 also included in numerous theories about firm growth, such as in the stochastic theory of Simon and Bonini (1958), who assumed Gibrat's Law to apply for firms above the minimum efficient size level, and in a model of capital adjustment made by Lucas (1967), who supposed 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 following 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 only after they have entered the market. Since the older firms have already learned about their efficiency and are not in need of further growth, small and young firms grow faster. The testable and excessively tested (see below) hypotheses that firm growth decreases with age when firm size is held constant can hence be directly drawn from Jovanovic's model.
As young firms usually start below their minimum efficient size, models of optimum firm size predict young and small firms to grow fast in order to obtain their minimum efficient size. Growth is absolutely essential if firms operate in industries with relevant economies of scale. Additionally, start-ups with a smaller initial size will have a greater need to grow (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 mainly rejected for the U.S. (Sutton, 1998), but also for most countries in Europe (Audretsch et al., 1999). Mansfield's (1962) conjecture, that the early empirical rejection of Gibrat's Law is a statistical artifact, because it is driven by a "sample censoring" problem, which is caused by a higher likelihood of exit by small firms with low growth rates, was addressed in literature in the later 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) also found that firms' growth rates are decreasing in size, i.e. a robust rejection of the Law of Proportional Effects. This 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 either high, medium or low technological sectors in equal measure. By contrast, the evidence for service sectors is ambiguous, since in some cases either growth rates are independent of firm size for a subsample of the firms investigated (Audretsch et al., 2004) or Gibrat's Law is clearly rejected (Petrunia, 2008). 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 employment in the beginning period on employment in the following periods 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 early years following entry.

The violation of Gibrats Law seems to become less severe for larger firms (Evans, 1987a). Hall (1987) even finds Gibrat's Law accepted for the larger firms in her sample. Recent research (Lotti et al., 2008) 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. the firm's employment growth follows Gibrat's Law after the firm has been fully developed. Because of that 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 concurrently also the influence of firm age on employment growth and find that the growth decreases not only with firm size, but also with firm age.

Not least because of the bulk of investigations and the mostly consistent results, the correlation of firm size and age with firm growth has become one of "stylized results of entry" (see Geroski, 1995).

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, which are not as often made as on the aggregate level, are based on the Community Innovation Survey (CIS), a harmonized innovation survey on the European level. These studies concentrate on mostly matured small and medium establishments with more than 10 employees. Studies investigating the effect of innovation activities on employment growth of extremely young 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. For process innovations direct supply-side effects in form of labor-saving productivity gains allow a firm to produce the same output with less

[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.

labor. The employment growth might thus be lower. But if the firm passes on cost advantages to customers through price reductions, positive (indirect) demand-side effects arise in form of increased demand. If the demand-side effects compensate for the negative effect of labor-saving productivity gains, the effect of process innovations on employment growth can even be positive.

Similarly, two opposing effects of product innovation and market novelties on labor demand can be distinguished. On the one hand the introduction of new products stimulates new demand for a firm's products and thus increases firm's labor demand. On the other hand 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. raising the price above marginal costs by output reduction, and reducing labor demand (Smolny, 1998; Blechinger et al., 1998). The theoretical model by Katsoulacos (1986) derives a positive total effect of product innovations and a total negative 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 process or product innovations and market novelties are used as direct output measures. Patents can be seen as intermediate innovation output as they are often claimed to be only 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. Some studies find a positive effect for process innovations, too (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) found that patenting has a positive effect on the employment growth, Calvo (2006) stated that both process and product innovations have a strong positive influence on the employment growth in young Spanish firms.

Concerning the legal form, firms with limited liability are expected to show up higher growth potentials. Owners of those firms are not liable with their own fortune. Therefore incentives for taking riskier projects, which yield higher returns on investment, are higher for firms with limited liabilities conditional on surviving (Stiglitz and Weiss, 1981). This relation is supported in studies by Harhoff et al. (1998) and Davidsson et al. (2002) 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 can be seen in terms of employment growth and the 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 firm 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.

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 promising business plan, i.e. to direct investment towards those areas of business activity that will generate the highest returns. Greater human capital increases founders' productivity in terms of organizing and managerial efficiency and acts as a positive signal for the firms's prospective stakeholders (investors, customers and suppliers). These parties usually have imperfect information about the firms' potentials and will benchmark the firms by means of observable characteristics they pull together with firm success. Therefore, firm success should be higher for the founders with a rich human capital endowment (Brüderl and Preisendörfer, 1992; Bosma et al., 2004).

A formalized model of human capital's impact on a firm's labor demand was made by van Praag and Cramer (2001). 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 with Dutch data confirms the predictions of their theoretical model.

Following Becker (1995), human capital is traditionally distinguished in general human capital and specific human capital. In entrepreneurship research general human capital is usually measured in terms of schooling and 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. The higher the human capital endowment of the founders, the higher the survival probabilities are found to be. Concerning work experience, a concave relationship has been found (Brüderl and Preisendörfer, 1992). This concavity might be due to 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) found 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) showed that human capital measured by a technical degree of the founder(s) 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 also investigated in detail by Colombo and Grilli (2005), Bosma et al. (2004) and Koeller and Lechler (2006). They found that especially 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 not just a proxy 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 was investigated by Müller (2006). She found 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 causes higher employment growth in the future. 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 The depreciation of academic knowledge

The possibility of 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 (unemployment, sick leave) career interruptions have been frequently examined in terms of forgone earnings. The most common thing to do is to 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) noticed that depreciation of human capital's earning power may occur not only in periods of nonparticipation at the labor market, but at other times as well. Only a few studies (Groot, 1998; Arrazola and de Hevia, 2004) address the question of human capital depreciation during the times of employment, which has been usually specified in earning functions of earlier work, but has not yet been estimated explicitly. Non-linear methods enable Groot as well as Arrazola and de Hevia 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 for people working in high-tech and low-tech oriented industries. Furthermore, for highly-educated people, experience-earning profiles become steeper, i.e. the peak falls faster with increasing education. This procedure implicitly assumes that human capital depreciation due to workers' aging and the obsolescence of knowledge is also present 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 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 paper 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 being used continuously. Furthermore, scientific techniques might become obsolete and their 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-up founders is determined by the stock of their *academic knowledge* and the stock of their *professional experience*.

During the time in academia academic knowledge is accumulated. At the moment when the academic institution is left, the stock of a person's academic knowledge is assumed to be 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. One can thus assume that $A(t) > 0$ 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, $P(t) > 0$ with $\frac{\partial P(t)}{\partial t} > 0$ 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 $HC(t) = \min\left[\alpha A(t), \beta P(t)\right]$, where $\alpha > 0$ 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 $-\frac{\frac{\partial^2 A(t)}{\partial t^2}}{\frac{\partial^2 P(t)}{\partial t^2}} < \frac{\beta}{\alpha}$, $\frac{\partial^2 A(t)}{\partial t^2} < 0$ 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 ts 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 1). This is reasonable since some basic skills which have been learned at university remain present even after decades.
Figure 1 illustrates how total human capital is composed of academic knowledge and professional experience. The upper graph depicts how professional experience might be 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 time that elapses between leaving the university and starting a venture 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 1 illustrates the combined effect of the time after leaving academia, but before founding, on the total human capital endowment of the (prospective) entrepreneur. 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 the development if academic knowledge and professional experience are perfect substitutes and if the second order condition is fulfilled. At the beginning total human capital is increasing. At some point in time human capital peaks and decreases thereafter. Because total human capital of the founders is directly linked to employment growth, those 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 paper states the following:

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

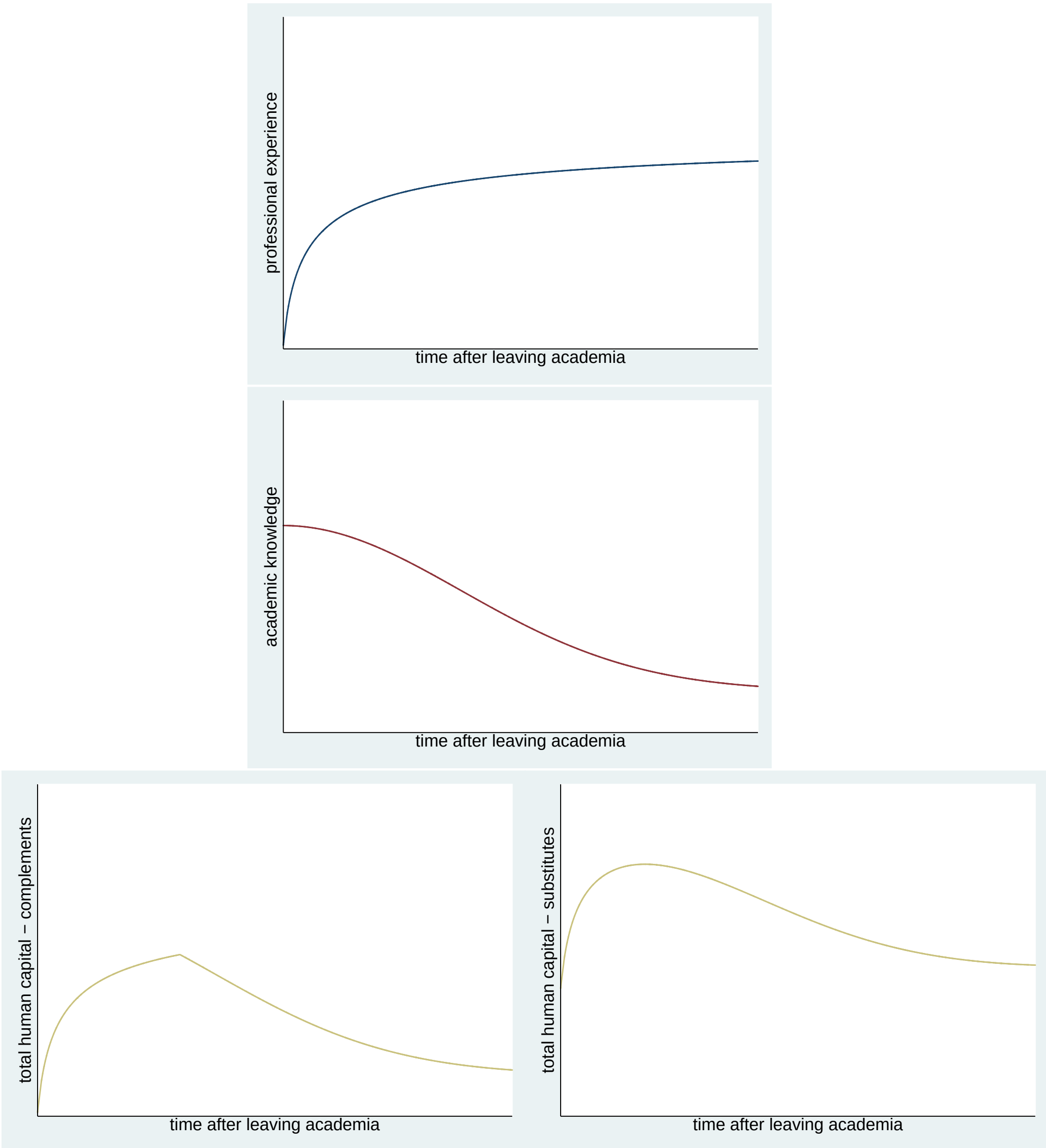


Figure 1: Graphical illustration - Founder's human capital development after leaving university

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.

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") technology changes and catching-up processes require starting the venture earlier. Speaking in terms of the graph at the bottom of Figure 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 her academic institution on firm's employment growth is inverse u-shaped* ***and differs between academic start-ups and academic spin-offs****.*

4 Empirical Analysis

4.1 Growth model and estimation method

Employment growth of academic start-ups is modeled following an exponential growth path as 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_{2008} at the beginning of 2008 is determined as following:

$$S_{2008} = [exp(\boldsymbol{X\beta}) \cdot G(A_{2008}, S_T)]^{A_{2008}}(S_T)e. \quad (1)$$

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

[2]See section 4.2 for a detailed description of the variables included.

Taking logarithms and rearranging yields for the annual growth rate

$$\boldsymbol{y} = \frac{ln(S_{2008}) - ln(S_T)}{A_{2008}} \quad = \quad \boldsymbol{X\beta} + ln(G(A_{2008}, S_T)) + \boldsymbol{u}. \tag{2}$$

Equation 2 is estimated using quantile regressions. This estimation technique of modeling 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. Frequently cited in this context are Mosteller and Turkey (1977, p. 266): "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."
But investigating young firm's growth we are especially interested in the determinants of especially high growth as well as in the causes of being at the lower tail of the growth distribution. Quantile regressions therefore 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. Firstly, the inference in the quantile regression framework is robust to distributional assumptions. In fact, inferential statistics can be obtained distribution-free. Likewise quantile regressions are especially suitable for heteroscedastic data. Secondly, for highly-skewed or heavy-tailed distributions the mean does not only give an incomplete picture of the distribution, 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. 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 or 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

$$\begin{aligned} y_i &= x_i\boldsymbol{\beta_\theta} + ln(G_\theta(A_{i2008}, S_{iT})) + u_{\theta i} \\ &\text{with} \quad Q_\theta(y_i|x_i, A_{i2008}, S_{iT}) = x_i\boldsymbol{\beta_\theta} + ln(G_\theta(\circ)). \end{aligned} \quad (3)$$

Q_θ denotes the θth conditional quantile of firm's 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.

$$\begin{aligned} \min_{\boldsymbol{\beta}} \sum_{i:y_i \geq x_i\boldsymbol{\beta}+ln(G_\theta(A_{i2008},S_{iT}))} \theta \quad |y_i - x_i\boldsymbol{\beta} - ln(G_\theta(A_{i2008}, S_{iT}))| + \\ \sum_{i:y_i < x_i\boldsymbol{\beta}+ln(G_\theta(A_{i2008},S_{iT}))} (1-\theta) \quad |y_i - x_i\boldsymbol{\beta} - ln(G_\theta(A_{i2008}, S_{iT}))|. \end{aligned}$$

Interpreting coefficients estimated by quantile regressions is as easy 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 in the quantile regression framework. Additionally, for quantile regressions the monotonic equivariance property allows to easily calculate the effect of a regressor on the dependent variable in absolute terms even when regressors or the independent variable enter the model in logarithmic terms. This does *not* hold for OLS regressions.

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

4.2 Database and Descriptive Statistics

The following 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 Foundation 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 was 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 this paper is to investigate the human capital depreciation of academic founders only academic start-ups (start-ups of either 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 presented in section 4.3. Using only academic start-ups for the analysis implies that the founders of those start-ups have a similar educational level. This fact allows me to distinguish the depreciating effects on human capital of the time which

[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. (2003); Müller (2008).

[5]In case of establishments in teams the year when the *last* founder left academia was recorded.

elapses after leaving academia and their influence on employment growth.

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. (2003) following Mansfield's (1995) method in identifying technology transfer from academic research concerning the development of new products and processes. Using this approach the sample of 4.303 academic start-ups contains 301 academic spin-offs.

According to the growth model presented in section 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 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 1).

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

The central variable which is investigated in this paper, the time that elapses between leaving academia and starting a venture, is measured in categories. This is done for the following reason: The founders might have still been in academia when the firm was founded but they might have already left university before the survey was carried out. That applies for around 9 percent of all start-ups in the sample. For those firms a negative time-lag can be calculated. But the founders of further 8 percent of the start-ups have

[6]Earlier work has classified this type of academic start-ups as transfer spin-offs (see Egeln et al., 2003; Müller, 2008).

Table 1: Non-normality 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.

been still in academia, when the survey was conducted. For those firms we know that their time-lag is negative, but we do not know the exact value so far.[7] 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. For the analysis six categories of the time-lag between leaving academia and firm formation are built and included in the analysis using dummies. The category of a time-lag from zero up to two years was used 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, measuring if the start-up can be classified as a spin-off, are included in the regressions. Most academic start-ups have an time-lag of 11-20 years (see Table 2). This is not surprising since the average age of founders in Germany is around 40

[7] An example will help to understand that censoring problem: If the founder was still in academia when the firm was founded due to the survey design two possible cases might occur: (1) 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. (2) For those founders who have established their business, e.g. 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 negative.

years. A non-negligible fraction of academic start-ups is either founded while at least one of the founders still has been in academia (17 percent) or shortly after leaving academia (10 percent).

Table 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.

In developing the hypotheses I assumed that after leaving academia founders of academic start-ups accumulate professional experience as well as industry experience, but are exposed to a depreciation of their academic knowledge. If founders experienced unemployment during that time not as much professional experience could have been acquired as supposed by their time-lag. Even a depreciation of their human capital gained by means of professional experience could have taken place. For this reason a further dummy variable is included in the analysis which indicates if one of the founders was confronted with a longer unemployment spell.

In order to control for the well documented relationship between size, age and employment growth and to test for the validity of Gibrat's Law for young firms in the research- and knowledge-intensive industries, initial firm size and 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 was 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 measuring if the firm is active in exporting, if 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.

Innovative activities of the start-ups are captured by three dummy variables measuring as well innovative input and output. Two of them show if the start-up is conducting continuous or occasional R&D, the other dummy variable indicates if the start-up has introduced novelties to the market.

In the past determinants of employment growth of young firms have been investigated almost solely in the conditional mean framework, mostly using OLS or discrete response models (for growth categories), sometimes with procedures controlling for potential selection biases. Therefore this study not only contributes to the investigation of the effect of entrepreneur's human capital depreciation on firm's employment growth, but also to the assessment of the effect of variables which have been frequently used in growth regression on the median of the distribution of employment growth. 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 the analysis presented 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 firm's 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 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 or the Chamber of Industry and Commerce. Public funding from the Federal Employment Agency (Bundesagentur für Arbeit - BA) is granted to unemployed persons who start their own business. The volume of financial support from the BA is rather low as it primarily aims to ease the transition into self-employment and to ensure the founder's cost of living in the first months. The dummy might thus not only capture a potential relaxation of financial constraints but poor growth prospects of start-ups aimed to get out of dire straits. Around 10 percent

of the 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. For that reason funding amounts are considerably larger and thus more likely to be able to relax financial constraints.
Another way of public, though non-financial support is housing of new ventures in science parks or business incubators. 6 percent of all academic start-ups in the sample have in fact 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 investigated in this paper 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, technological services and knowledge-intensive services[8]. High-technology industries are those industrial sectors which exhibit an average R&D-intensity above 3.5%, 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 technological 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,

[8]A classification list based on NACE codes can be provided on request by the author.

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.

4.3 Estimation Results

Equation 3 was 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 and compared to OLS regression of the same model. Both for the OLS regression and for the median regression the hypothesis of human capital depreciation of academic founders once university is left is confirmed. The impact of the time-lag after university has been left is in fact 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. When 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 as 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 is 1.7 percent ($= 0.040 + (-0.057)$) lower than 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 product and firm's development. This result is in line with an observation of Doutriaux (1987). He finds that manufacturing firms grow less if the academic is still employed by the university.

Table 3: OLS and Median Regression on employment growth

	OLS		Q50	
	coeff.	se	coeff.	se
Time-lag since academia was left				
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)
Size and foundation year				
ln(size)	-0.070***	(0.010)	-0.014	(0.010)
$\ln(size)^2$	0.000	(0.003)	-0.011***	(0.003)
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)
Limitation of 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)
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)
High-technology industries	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.

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

Table 4 shows the regression results for the most, however due to shortage of space, only selected quantiles. It can be seen that 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, for growing firms differences 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 seems to have 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 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 0. The elasticity of end-of-period firm size with respect to beginning-of-period firm age 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[9]. 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

[9]This is another test of Gibrat's Law. Gibrat's Law holds if a one percent increase in initial size gives rise to an increase in "end-of-period employment" (employment in 2008) of one percent.

distribution. In fact it can be rejected for all regressions from the 25 percent quantile up to the 70 percent quantile (see Table 6 in the appendix).

The year of foundation significantly influences annual employment growth. Growth rates are highest for those 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 quantiles also include growing firms (from the 40 percent quantile on).

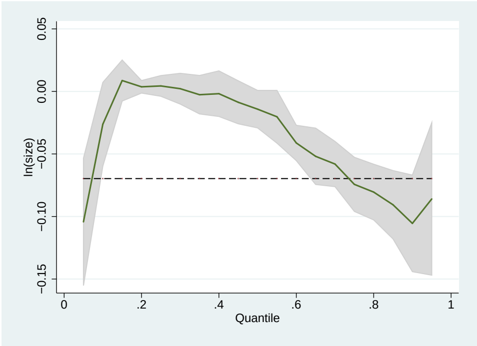
Furthermore, coefficients composing the size-age-growth relationship vary sizeably from quantile to quantile when coefficients are compared along the growth distribution (see Figure 2). Differences of the coefficient *ln(size)* are statistically significant between the 60 percent quantile and the higher quantiles. Moreover, almost all coefficients for the "2003-2006 year of foundation-dummies" differ significantly from quantile to quantile. 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). 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.

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. But 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.

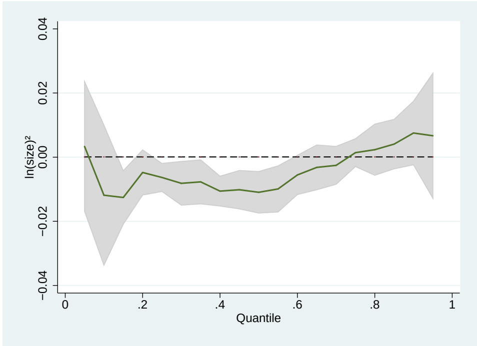
Table 4: Results of quantile regressions on employment growth, selected quantiles

	Q5	Q10	Q25	Q40	Q50	Q60	Q70	Q75	Q80	Q90	Q95
Time-lag since academia was left											
Still in science	-0.007	-0.000	-0.000	0.006	0.007	0.003	0.007	0.016	0.012	0.021	0.024
Time-lag: 3-5 years	0.001	0.000	-0.000	0.027**	0.040***	0.047***	0.047***	0.056***	0.057***	0.060***	0.070**
Time-lag: 6-10 years	0.005	-0.000	-0.000	0.017**	0.030**	0.023*	0.026**	0.036***	0.035**	0.042**	0.050*
Time-lag: 11-20 years	-0.004	-0.000	0.000	0.006	0.006	0.006	0.005	0.016	0.015	0.029*	0.038
Time-lag: +20 years	-0.039*	0.000	-0.006*	-0.022***	-0.024**	-0.034***	-0.040***	-0.026*	-0.030*	-0.021	-0.011
(Spin-off)*(still in science)	-0.001	-0.029	-0.012	-0.028	-0.034*	-0.043**	-0.056**	-0.062**	-0.039	-0.025	-0.056
(Spin-off)*(0-2 years)	-0.005	-0.000	-0.003	-0.030	-0.020	-0.015	0.018	0.022	0.020	0.015	-0.003
(Spin-off)*(3-5 years)	-0.057	0.000	-0.006	-0.028	-0.057*	-0.081*	-0.083*	-0.064	-0.085*	-0.097	-0.077
(Spin-off)*(6-10 years)	-0.085**	-0.006	-0.009	-0.053***	-0.096***	-0.092***	-0.111***	-0.098***	-0.101**	-0.065	-0.074
(Spin-off)*(11-20 years)	0.012	-0.029	-0.013	-0.013	0.029	-0.001	-0.018	-0.016	-0.035	-0.004	-0.040
(Spin-off)*(+20 years)	0.046	0.000	0.003	-0.001	-0.019	0.014	0.027	0.030	0.028	0.087	0.040
Size and foundation year											
ln(size)	-0.104***	-0.026	0.004	-0.002	-0.014	-0.041***	-0.058***	-0.074***	-0.080***	-0.105***	-0.086***
ln(size)^2	0.003	-0.012	-0.006**	-0.011***	-0.011***	-0.006*	-0.003	0.001	0.002	0.008	0.007
Founded in 2002	0.003	-0.000	-0.000	0.010	0.013*	0.018**	0.017*	0.017*	0.020*	0.029**	0.046**
Founded in 2003	-0.006	-0.000	-0.000	0.019***	0.026***	0.041***	0.049***	0.057***	0.060***	0.070***	0.084***
Founded in 2004	-0.003	0.000	-0.000	0.025***	0.040***	0.061***	0.081***	0.091***	0.094***	0.124***	0.147***
Founded in 2005	-0.010	-0.000	-0.000	0.036***	0.070***	0.113***	0.145***	0.160***	0.186***	0.248***	0.297***
Founded in 2006	0.001	0.000	-0.000	0.019**	0.049***	0.119***	0.173***	0.193***	0.219***	0.363***	0.467***
Innovation activities											
Continuous R&D	-0.002	-0.000	0.006	0.012	0.016*	0.030***	0.043***	0.038***	0.042***	0.036**	0.033
Occasional R&D	-0.010	0.000	-0.000	0.002	-0.002	0.008	0.011	0.007	0.011	0.002	0.027
Market novelties	0.005	0.000	0.006	0.029***	0.036***	0.034***	0.029***	0.032***	0.031***	0.047***	0.059***
Science park	0.005	-0.000	0.059***	0.044***	0.029**	0.036**	0.029**	0.027*	0.013	0.026	0.038
Public funding (BA)	0.006	0.000	-0.000	-0.018***	-0.038***	-0.039***	-0.021	-0.022*	-0.033**	-0.038**	-0.038
Public funding (non BA)	0.019**	0.000	0.018*	0.033***	0.033***	0.026***	0.026***	0.021**	0.022*	0.023	0.023
Limitation of liability	0.005	0.000	0.006	0.043***	0.053***	0.058***	0.057***	0.063***	0.063***	0.074***	0.088***
Exports	0.012*	-0.000	0.006	0.044***	0.057***	0.058***	0.062***	0.058***	0.063***	0.056***	0.065***
Team	0.038**	0.024**	0.003	0.007	0.004	-0.000	-0.007	-0.008	-0.006	-0.002	-0.022
No-expansion strategy	-0.013*	0.000	-0.006	-0.030***	-0.056***	-0.067***	-0.060***	-0.063***	-0.074***	-0.083***	-0.081***
Unemployed	-0.046	-0.024	-0.003	-0.014	-0.027	-0.058***	-0.071***	-0.079***	-0.085***	-0.128***	-0.119**
Contacts to academia											
Joint research	0.012	0.033	0.060***	0.015	-0.001	-0.013	-0.017	-0.004	-0.015	-0.028	-0.019
Contract research	0.013	0.024	0.007	0.007	-0.000	-0.004	-0.008	-0.026	-0.044*	-0.026	-0.035
Customer	0.007	0.000	0.000	0.018*	0.018*	0.026*	0.024*	0.024	0.038*	0.047**	0.050
Continuing education	0.026	-0.000	0.006	0.037**	0.045***	0.044**	0.065***	0.051***	0.043***	0.034	0.047
High-technology industries	-0.001	0.000	0.003	0.015**	0.018**	0.025***	0.021**	0.024**	0.019*	0.010	0.016
Knowledge-intensive services	-0.002	-0.000	-0.000	0.004	0.008	0.022***	0.019**	0.019**	0.020**	0.013	0.019
Constant	-0.011	-0.002	0.000	-0.001	0.031**	0.067***	0.108***	0.128***	0.157***	0.219***	0.231***
Pseudo R^2	0.146	0.044	0.011	0.094	0.113	0.124	0.141	0.150	0.163	0.201	0.239

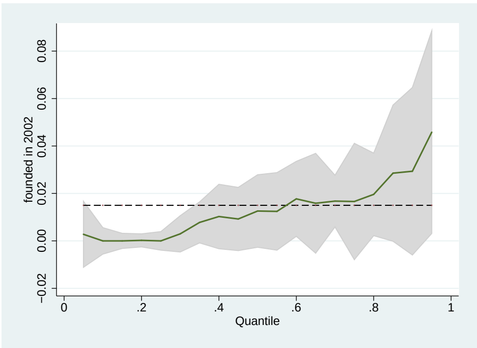
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, based on bootstrapped standard errors with 500 replications. 4303 Observations.
Source: ZEW Spin-Off Survey 2008, author's calculations.



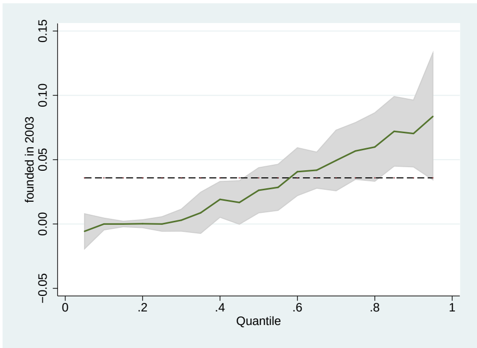
(a) $ln(size)$



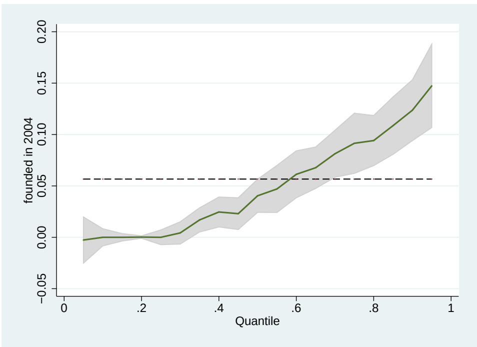
(b) $ln(size)^2$



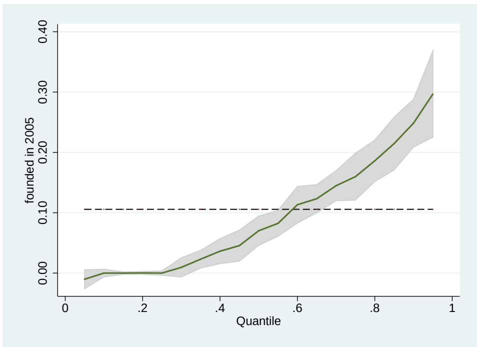
(c) Founded in 2002



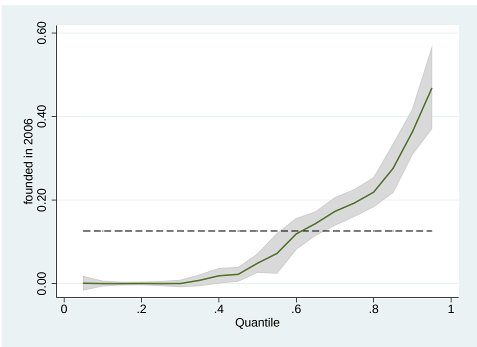
(d) Founded in 2003



(e) Founded in 2004



(f) Founded in 2005



(g) Founded in 2006

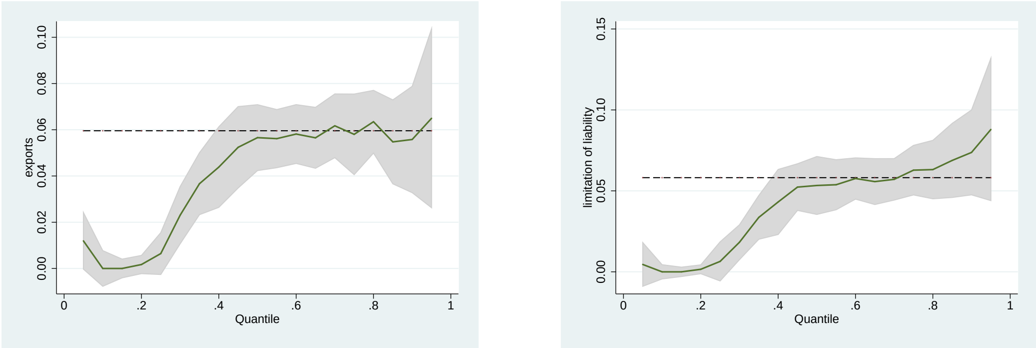
Figure 2: Variation in the coefficients of size and year of foundation

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.

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 the effect of 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). 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 regression results reveal the high effect of the variable *science park* 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).

A limitation of liability exerts a positive stimulus on employment growth. This effect is significantly growing from a 4 percent stimulus at the 25% quantile up to a 9 percent stimulus at the 95% quantile (see Figure 3). 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.



(a) Exporting (b) Limitation of liability

Figure 3: Variation in the coefficients *exports* and *limitation of 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.

Controlling regressors for firm strategies which are not growth-oriented, industry effects and longer unemployment spells during the time after graduation or working in research 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 4).

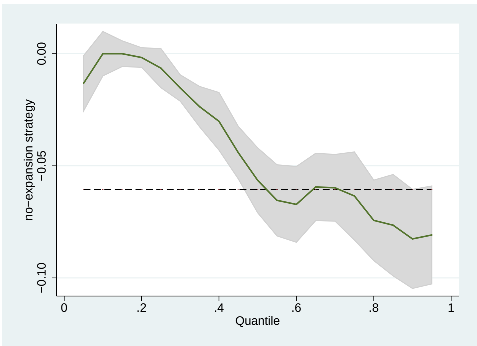


Figure 4: Variation in the coefficient *no-expansion strategy*

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 in the cases where academia is a firm's customer or where firm's employees receive 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 7 in the appendix). Some coefficients get larger when excluding the variables *limitation of liability*, *exports*, *team*, *no-expansion strategy* and *unemployed*. This result is reasonable since most of these coefficients have been shown to exert important influence on employment growth. When these variables are excluded the effect is captured by the error term or other variables correlated with the excluded variables.

5 Conclusions

This paper 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 was 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 should 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 especially needed in the early stages of product's and firm's development.

Furthermore, the determinants of academic start-up's employment growth are examined along the whole distribution of young firm's employment growth. I find that 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 limitation of 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 firm's employment growth. This result is a material contribution to the literature of young firm's growth since the validity of Gibrat's Law was mainly tested in the conditional mean framework.

References

Acs, Z., L. Anselin, and A. Varga (2002): "Patents and innovation counts as measures of regional production of new knowledge," *Research Policy*, 31, 1069—-1085.

Almus, M. (2002): "What characterizes a fast-growing firm?" *Applied Economics*, 34, 1497–1508.

Almus, M. and E. Nerlinger (1999): "Growth of New Technology-Based Firms: Which Factors Matter?" *Small Business Economics*, 13, 141–154.

——— (2000): "Testing "Gibrat's Law" for Young Firms - Empirical Results for West Germany," *Small Business Economics*, 15, 1–12.

Arrazola, M. and J. de Hevia (2004): "More on the estimation of the human capital depreciation rate," *Applied Economic Letters*, 11, 145–148.

Audretsch, D., L. Klomp, E. Santarelli, and A. Thurik (2004): "Gibrat's Law: Are Services Different?" *Review of Industrial Organization*, 24, 301–324.

Audretsch, D., E. Santarelli, and M. Vivarelli (1999): "Start-up Size and Industrial Dynamics: Some Evidence from Italian Manufacturing," *International Journal of Industrial Economics*, 17, 965–983.

Beblo, M. and E. Wolf (2000): "How much does a year off cost? Estimating the wage effects of employment breaks and part-time periods," ZEW Discussion Paper 00-68.

Becchetti, L. and G. Trovato (2002): "The Determinants of Growth for Small and Medium Sized Firms: The Role of the Availability of External Finance," *Small Business Economics*, 19, 291–306.

Becker, G. (1995): *Human Capital*, NBER, 2nd ed.

Bernard, A. and J. Jensen (1999): "Exceptional exporter performance: cause, effect, or both?" *Journal of International Economics*, 47, 1–2.

Blechinger, D., A. Kleinknecht, G. Licht, and F. Pfeiffer (1998): "The Impact of Innovation on Employment in Europe - An Analysis using CIS Data," ZEW Documentation 98-02.

Bosma, N., M. van Praag, R. Thurik, and G. de Witt (2004): "The Value of Human and Social Capital Investments for the Business Performance of Startups," *Small Business Economics*, 23, 227–236.

Brüderl, J. and P. Preisendörfer (1992): "Survival Chances of Newly Founded Business Organizations," *American Sociological Review*, 57, 227–239.

Buchinsky, M. (1998): "Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research," *The Journal of Human Resource*, 33, 88–126.

Bürgel, O., A. Fier, G. Licht, and G. Murray (2004): *The Internationalisation of Young High-Tech Firms*, Mannheim: Physica.

Cabral, M. and J. Mata (2003): "On the Evolution of the Firm Size Distribution: Facts and Theory," *American Economic Review*, 93, 1075–1090.

Calvo, T. (2006): "Testing Gibrat's Law for Small, Young and Innovating Firms," *Small Business Economics*, 26, 117—-123.

Cameron, C. and P. Trivedi (2009): *Microeconometrics using Stata*, College Station, Texas: Stata Press.

Colombo, M. and L. Grilli (2005): "Founders' Human Capital and the Growth of New Technology-Based Firms: A Competence-Based View." *Research Policy*, 34, 795–816.

Davidsson, P., B. Kirchhoff, A. Hatemi-J, and H. Gustavsson (2002): "Empirical Analysis of Business Growth Factors Using Swedish Data," *Journal of Small Business Management*, 40, 332–349.

Doutriaux, J. (1987): "Growth pattern of academic entrepreneurial firms," *Journal of Business Venturing*, 2, 285–297.

Dunne, T. and A. Hughes (1994): "Age, Size, Growth, and Survival: UK Companies in the 1980s," *The Journal of Industrial Economics*, 42, 115–140.

Dunne, T., M. Roberts, and L. Samuelson (1989): "The Growth and Failure of U.S. Manufacturing Plants," *The Quarterly Journal of Economics*, 104, 671–698.

Egeln, J., S. Gottschalk, C. Rammer, and A. Spielkamp (2003): "Public Research Spin-offs in Germany," ZEW Documentation 03-04.

Eisenhardt, K. and C. Schoonhoven (1990): "Organizational Growth: Linking Founding Team, Strategy, Environment and Growth among U.S. Semiconductor Ventures, 1987-1988," *Administrative Science Quarterly*, 35, 504–529.

Engel, D. (2002): "The Impact of Venture Capital on Firm Growth: An Empirical Investigation," ZEW Discussion Paper 02-02.

Ericson, R. and A. Pakes (1995): "Markov-perfect industry dynamics: A framework for empirical work," *Review of Economic Studies*, 62, 53–82.

Evans, D. (1987a): "The Relationship Between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries," *Journal of Industrial Economics*, 35, 567–581.

——— (1987b): "Tests of Alternative Theories of Firm Growth," *Journal of Political Economy*, 95, 657–674.

Fotopoulos, G. and H. Louri (2004): "Corporate growth and FDI: are multinationals stimulating local industrial development?" *Journal of Industry, Competition and Trade*, 4, 163–189.

Geroski, P. A. (1995): "What do we know about entry?" *International Journal of Industrial Organization*, 13, 421–440.

Gibrat, R. (1931): *Les Inegalites Economiques*, Paris: Librairie du Recueil Sirey.

Görlich, D. and A. de Grip (2007): "Human Capital Depreciation During Family-related Career Interruptions in Male and Female Occupations," Kiel Working Paper 1379.

Greenan, N. and D. Guellec (2000): "Technological Innovation and Employment Reallocation," *Labour*, 14, 547–590.

Groot, W. (1998): "Empirical estimates of the rate of depreciation of education," *Applied Economic Letters*, 5, 535–538.

Hall, B. (1987): "The Relationship Between Firm Size and Firm Growth in the US Manufacturing Sector," *Journal of Industrial Economics*, 35, 583–606.

Hao, L. and D. Naimann (2007): *Quantile Regression*, Quantitative Applications in the Social Sciences, Thousand Oaks: SAGE Publications.

Harhoff, D., K. Stahl, and M. Woywode (1998): "Legal Form, Growth and Exit of West German Firms - Empirical Results for Manufacturing, Construction, Trade and Service Industries," *Journal of Industrial Economics*, 46, 453–488.

Harrison, R., J. Jaumandreu, J. Mairesse, and B. Peters (2008): "Does Iinnovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data From Four European Countries," NBER Working Paper 14216.

Jaumandreu, J. (2003): "Does innovation spur employment? A firm-level analysis using Spanish CIS data," mimeo, Universidad Carlos III de Madrid.

Jovanovic, B. (1982): "Selection and Evolution of Industry," *Econometrica*, 50, 649–670.

Katsoulacos, Y. (1986): *Technical Change and the Labour Market: A Theoretical Study of the Employment Effects of Product and Process Innovation*, Brighton: Oxford University Press.

Koeller, C. and T. Lechler (2006): "Employment Growth in High-Tech New Ventures," *Journal of Labor Research*, 27, 135–147.

Koenker, R. and G. Bassett (1978): "Regression Quantiles," *Econometrica*, 46, 33–50.

Koenker, R. and K. Bassett (2001): "Quantile Regression," *Journal of Economic Perspectives*, 15, 143–156.

Lachenmaier, S. and H. Rottmann (2007): "Effects of Innovation on Employment: A Dynamic Panel Analysis," CESifo Working Paper 2015.

Lotti, F., E. Santarelli, and M. Vivarelli (2003): "Does Gibrat's Law hold among young, small firms?" *Journal of Evolutionary Economics*, 13, 213–235.

——— (2008): "Defending Gibrat's Law as a long-run regularity," *Small Business Economics*, forthcoming.

Lucas, R. (1967): "Adjustment Costs and and the Theory of Supply," *Journal of Political Economy*, 75, 321–343.

——— (1978): "On the Size Distribution of Business Firms," *The Bell Journal of Economics*, 9, 508–523.

Mansfield, E. (1962): "Entry, Gibrat's Law, Innovation, and the Growth of Firms," *The American Economic Review*, 52, 1023–1051.

——— (1995): "Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing," *The Review of Economics and Statistics*, 77, 55–65.

Mincer, J. (1974): *Schooling, Experience and Earnings*, New York: Columbia University Press.

MINCER, J. AND H. OFEK (1978): “Interrupted Work Careers: Depreciation and restoration of human capital,” *The Journal of Human Resources*, 17, 3–24.

MINCER, J. AND S. POLACHEK (1974): “Family Investments in Human Capital: Earnings of Woman,” *The Journal of Political Economy*, 82, 76–108.

——— (1978): “An Exchange: The Theory of Human Capital and the Earnings of Women: Women’s Earnings Reexamined,” *The Journal of Human Resources*, 13, 118–134.

MOOG, P. (2004): *Humankapital des Gründers und Erfolg der Unternehmensgründung*, Wiesbaden: Deutscher Universitäts-Verlag.

MOSTELLER, F. AND J. TURKEY (1977): *Data Analysis and Regression: A Second Course in Statistics*, Reading Mass: Addison-Wesley.

MÜLLER, B. (2006): “Human Capital and Successfull Academic Spin-Off,” ZEW Discussion Paper 06-81, Centre for European Economic Research.

MÜLLER, K. (2008): “University Spin-Off’s Transfer Speed – Analyzing the Time from Leaving University to Venture,” ZEW Discussion Paper 08-34, Centre for European Economic Research.

NESLON, R. AND S. WINTER (1982): *An Evolutionary Theory of Economic Change*, Cambridge, Mass.: Harvard Univ. Press.

NEUMANN, S. AND A. WEISS (1995): “On the Effects of Schooling Vintage on Experience-Earnings Profiles: Theory and Evidence,” *European Economic Review*, 39, 943–955.

NIEFERT, M. (2005): “Patenting Behaviour and Employment Growth in German Start-up Firms,” ZEW Discussion Paper 05-03, Centre for European Economic Research.

OLIVEIRA, B. AND A. FORTUNATO (2006): “Firm Growth and Liquidity Constraints: A Dynamic Analysis,” *Small Business Economics*, 27, 139–156.

PETERS, B. (2004): “Employment Effects of Different Innovation Activities: New Microeconometric Evidence,” ZEW Discussion Paper 04-73.

Petrunia, R. (2008): "Does Gibrat's Law Hold? Evidence from Canadian Retail and Manufacturing Firms," *Small Business Economics*, 30, 201–214.

Regev, H. (1998): "Innovation, Skilled Labour, Technology and Performance in Israeli Industrial Firms," *Economics of Innovation and New Technology*, 5, 301–323.

Reichstein, T., M. Dahl, B. Ebersberger, and M. Jensen (2006): "The Devil Dwells in the Tails: A Quantile Regression Approach to Firm Growth," DRUID Working Paper No. 06-34, Copenhagen.

Reynolds, P. (1993): *High-Performance Entrepreneurship: What Makes it Different?*, Frontiers of Entrepreneurship Research, Babson College.

Simon, H. and C. Bonini (1958): "The Size Distribution of Business Firms," *American Economic Review*, 48, 607–617.

Smolny, W. (1998): "Innovations, Prices and Employment: A Theoretical Model and an Empirical Application for West German Manufacturing Firms," *The Journal of Industrial Economics*, 46, 359–381.

——— (2002): "Employment Adjustment at the Firm Level. A Theoretical Model and an Empirical Investigation for West German Manufacturing Firms," *The Journal of Industrial Economics*, 16, 65–88.

Stam, E., P. Gibcus, J. Telussa, and E. Garnsey (2007): "Employment Growth of New Firms," Scales Research Reports H200716, EIM Business and Policy Research.

Stiglitz, J. and A. Weiss (1981): "Credit Rationing in Markets with Imperfect Information," *American Economic Review*, 71, 393–410.

Storey, D. (1994): *Understanding the Small Business Sector*, London: Routledge.

Sutton, J. (1998): "Gibrat's Legacy," *Journal of Economic Literature*, 35, 40–59.

van Praag, C. and J. Cramer (2001): "The Roots of Entrepreneurship and Labour Demand: Individual Ability and Low Risk Aversion," *Economica*, 68, 45–62.

Van Reenen, J. (1997): "Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms," *Journal of Labor Economics*, 15, 255–284.

Wagner, J. (1992): "Firm Size, Firm Growth, and Persistence of Chance: Testing GIBRAT's Law with Establishment Data from Lower Saxony, 1978-1989," *Small Business Economics*, 4, 125–131.

——— (2002): "The Causal Effects of Exports on Firm Size and Labor Productivity: First Evidence from a Matching Approach," *Economic Letters*, 77, 287–292.

Westhead, P. and D. Storey (1997): "Financial Constraints on the Growth of High Technology Small Firms in the United Kingdom," *Applied Financial Economics*, 7, 197–201.

Appendix

Table 5: Definition and descriptive statistics of all variables used

Variable	Definition	Mean	Std. dev.
Employment growth	Annual logarithmic change in employment between 2008 and the founding year	0.141	(0.210)
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 science)	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)
Size and year of foundation			
ln(size)	Logarithm of initial employment	0.859	(0.840)
$\ln(\text{size})^2$	Logarithm of initial employment squared	1.444	(2.329)
Founded in 2001	Start-up was founded in 2001 (Dummy)	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 5 – 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			
Limitation of 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-technology industries	Firm belongs to high-technology industries (average R&D intensity is above 3.5%) (Dummy)	0.241	(0.428)
Knowledge-intensive services	Firm belongs to knowledge-intensive service (Dummy)	0.405	(0.491)
Technological services	Firm belongs to technological service (Reference Category)	0.353	(0.478)

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

Table 6: 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: $\frac{\partial ln(S_{2008})}{\partial ln(S_t)} = 1 + A_{2008} \cdot \left[\beta_{ln(S_T)} + 2 \cdot \beta_{ln(S_T)^2} ln(S_T)\right] = 1$

Stars denote rejection at the following significance levels:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table 7: Robustness-checks: Median Regressions on employment growth

	Q50 (1)		Q50(2)		Q50(2)		Q50(4)		Q50(5)	
	coeff.	se	coeff.	se	coeff.	se	coeff.	se	coeff.	se
Time-lag since academia was left[1]										
Still in science	0.004	(0.010)	-0.000	(0.012)	0.000	(0.011)	-0.004	(0.012)	0.011	(0.011)
Time-lag: 3-5 years	0.036**	(0.014)	0.038**	(0.016)	0.032**	(0.014)	0.060***	(0.015)	0.042***	(0.014)
Time-lag: 6-10 years	0.025**	(0.011)	0.022*	(0.013)	0.023*	(0.012)	0.039***	(0.013)	0.032***	(0.012)
Time-lag: 11-20 years	0.008	(0.010)	0.002	(0.010)	0.001	(0.011)	0.011	(0.011)	0.009	(0.010)
Time-lag: +20 years	-0.024**	(0.011)	-0.029**	(0.012)	-0.028**	(0.012)	-0.032***	(0.011)	-0.020*	(0.012)
(Spin-off)*(still in science)			-0.035**	(0.017)	-0.031	(0.020)	-0.020	(0.026)	-0.025	(0.018)
(Spin-off)*(0-2 years)			-0.028	(0.026)	-0.011	(0.027)	-0.004	(0.034)	-0.016	(0.035)
(Spin-off)*(3-5 years)			-0.053*	(0.030)	-0.071**	(0.031)	-0.067	(0.042)	-0.063**	(0.029)
(Spin-off)*(6-10 years)			-0.098***	(0.033)	-0.099***	(0.031)	-0.082***	(0.026)	-0.091***	(0.030)
(Spin-off)*(11-20 years)			0.016	(0.029)	0.021	(0.028)	-0.028	(0.045)	0.020	(0.028)
(Spin-off)*(+20 years)			-0.002	(0.052)	-0.016	(0.040)	-0.004	(0.035)	-0.023	(0.041)
Size and year of foundation[2]										
ln(size)	-0.016	(0.010)	-0.013	(0.010)	-0.009	(0.010)	0.031***	(0.012)	-0.014	(0.010)
$\ln(\text{size})^2$	-0.010***	(0.003)	-0.011***	(0.003)	-0.012***	(0.003)	-0.018***	(0.004)	-0.011***	(0.003)
Founded in 2002	0.012	(0.007)	0.008	(0.007)	0.010	(0.007)	0.005	(0.007)	0.014*	(0.007)
Founded in 2003	0.024***	(0.008)	0.023***	(0.009)	0.021**	(0.008)	0.025***	(0.009)	0.027***	(0.008)
Founded in 2004	0.038***	(0.009)	0.037***	(0.009)	0.035***	(0.009)	0.036***	(0.012)	0.038***	(0.009)
Founded in 2005	0.068***	(0.012)	0.066***	(0.010)	0.065***	(0.011)	0.068***	(0.016)	0.071***	(0.012)
Founded in 2006	0.048***	(0.014)	0.042***	(0.014)	0.039***	(0.014)	0.043**	(0.019)	0.048***	(0.015)
Innovation activities										
Continuous R&D[3]	0.016*	(0.009)			0.019**	(0.008)	0.046***	(0.010)	0.021**	(0.010)
Occasional R&D[3]	-0.006	(0.010)			-0.000	(0.009)	0.020**	(0.010)	0.003	(0.009)
Market novelties	0.036***	(0.008)			0.033***	(0.008)	0.056***	(0.010)	0.036***	(0.007)
Science park	0.024*	(0.012)	0.039***	(0.014)			0.052***	(0.012)	0.036***	(0.013)
Public funding (BA)[4]	-0.037***	(0.010)	-0.037***	(0.010)			-0.040***	(0.010)	-0.039***	(0.010)
Public funding (non BA)[4]	0.031***	(0.008)	0.029***	(0.008)			0.040***	(0.009)	0.032***	(0.008)
Limitation of liability	0.054***	(0.008)	0.056***	(0.008)	0.055***	(0.009)			0.054***	(0.008)
Exports	0.056***	(0.007)	0.062***	(0.007)	0.060***	(0.007)			0.056***	(0.007)
Team	0.005	(0.008)	0.003	(0.007)	0.004	(0.008)			0.004	(0.008)
No-expansion strategy	-0.056***	(0.007)	-0.059***	(0.007)	-0.060***	(0.007)			-0.057***	(0.007)
Unemployed	-0.020	(0.018)	-0.032*	(0.019)	-0.030	(0.021)			-0.025	(0.020)
Contacts to academia										
Joint research	0.003	(0.017)	0.019	(0.013)	0.011	(0.015)	-0.002	(0.017)		
Contract research	-0.000	(0.021)	0.004	(0.020)	-0.003	(0.019)	0.022	(0.025)		
Customer	0.014	(0.012)	0.019*	(0.011)	0.014	(0.011)	0.018	(0.014)		
Continuing education	0.047***	(0.014)	0.045***	(0.013)	0.047***	(0.014)	0.055***	(0.019)		
High-technology industries[5]	0.018**	(0.009)	0.025***	(0.008)	0.025***	(0.009)	0.035***	(0.009)	0.020**	(0.008)
Knowledge-intensive services[1]	0.010	(0.007)	0.011	(0.007)	0.011*	(0.007)	0.025***	(0.009)	0.009	(0.007)
Constant	0.033***	(0.012)	0.046***	(0.013)	0.039***	(0.013)	0.004	(0.011)	0.030**	(0.012)
Observations	4303		4322		4308		4321		4303	
Pseudo R^2	0.111		0.107		0.108		0.073		0.111	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, bootstrapped standard errors (500 replications) in parentheses. Reference categories: (1) time-lag: 0-2 years, (2) founded in 2001, (3) no R& D (4) no public funding (5) technological services.
Source: ZEW Spin-Off Survey 2008, author's calculations.