7 PATENTING BEHAVIOR AND EMPLOYMENT GROWTH IN GERMAN START-UP FIRMS

A Panel Data Analysis

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1. Introduction

Innovation is universally regarded as a major source of economic growth. Correspondingly, innovation activities of firms are generally supposed to have a positive effect on firm performance. Product innovations increase demand; process innovations reduce marginal production costs. As a consequence, firms are able to conquer market shares at the expense of other firms and enhance their competitiveness. However, the time span of a competitive advantage is very short in highly competitive markets and continuous innovations are necessary to maintain a leading position. The positive relationship between innovation activities and economic performance is empirically less established at the firm level than at the macro-level.

There are quite a few studies analyzing the impact of R&D and innovations on productivity, sales, and market value at the firm level. However, despite the ongoing debate on the impact of technological change on employment, there is only relatively little microeconometric work dealing with the effect of innovations on corporate employment growth, particularly with respect to start-up firms. The sign of this effect, derived from theoretical models, is not clear: While increasing level of demand, product innovations might replace existing products and reduce price elasticity of demand so that output and employment may decrease as well; process innovations reduce production costs but often imply a labor-saving progress.

This paper empirically analyzes the relationship between innovative activity and employment growth at the micro-level using panel data on German start-up firms and patent data from the German Patent Office. It also describes the differences in entry patterns and post-entry performance following German reunification between Eastern and Western German firms and between patenting and non-patenting firms. Using fixed-effects and first-differencing panel methods, the effect of patenting activity and other potential determinants of post-entry performance is estimated.

The paper is structured as follows. The next section outlines the theoretical approaches and empirical results regarding the determinants of employment growth at the firm level while focusing on the effects of firm size, age, and innovative activity. The methodological problems encountered when analyzing the relationship between innovative activity and corporate growth as well as the econometric models used for the empirical analysis are subsequently described. A description of the underlying data set and the characteristics of Eastern and Western German start-ups as well as patenting and non-patenting start-ups follows. The last two sections present the results and the conclusion.

2. Determinants of Employment Growth

Turnover and labor costs are undoubtedly decisive factors determining level of employment. Innovations, however, are also among the most important determinants in many European economies (Blechinger et al., 1998). In contrast to the neoclassical growth theory, the theory of endogenous growth treats technological progress not as exogenously given but as a result of research and development efforts. Technological knowledge is disseminated and shared by the economy as a whole, promoting in turn economic growth. The importance which the theory of endogenous growth attaches to the production of technological knowledge for the growth process has increased interest in the microanalysis of innovation and its consequences for firm performance. Before turning to the effects of innovative activity on employment growth, however, an overview of theoretical approaches and empirical results regarding the size-growth and age-growth relationship is given.

2.1 The Effects of Firm Size and Age

The theoretical literature has paid special attention to the effect of firm size on corporate growth and to discussion of Gibrat's Law (Gibrat, 1931). According to this law, which is also called the Law of Proportionate Effect (LPE), firms grow proportionally and independently of their size. This implies that growth is independent of past growth, that growth rates are not heteroscedastic with firm size and that firm size distribution tends to become increasingly concentrated over time (Goddard et al., 2002).

Various theoretical approaches contradict Gibrat's Law. Models of optimum firm size postulate that firms converge to the minimum efficient size (MES), which varies with industry. Small firms operating below the MES have to grow to become competitive and survive. Large firms operating above the MES tend to shrink if the advantages of exploiting scale economies are outstripped by organizational problems. "Reversion-to-mean" effects and an approximation of firm sizes are then observed within industries. The need for start-up firms to grow depends on their start-up size and how prevalent scale economies are in the industry in question. The smaller a firm's start-up size relative to the MES, the more urgent it is for the firm to grow.

The model of "noisy selection" introduced by Jovanovic (1982) explains why most firms choose a start-up size below the optimal level. This theory emphasizes managerial efficiency and learning by doing as the key factors determining firms' growth dynamics. It assumes that new firms do not know their cost function in advance, but learn about their relative efficiency as soon as they enter the market. Given the information before entry, firms might be inclined to start with a suboptimal level of output to keep sunk costs low, to expand only if subsequent performance is encouraging and to leave the market otherwise. The model implies that surviving young and small firms grow faster than older and larger ones.

Models with Penrose (1959) effects suggest that firms' current-period growth rates are constrained. According to the "managerial-limits-to-growth" hypothesis, expansion carries an opportunity cost because some existing managers have to be diverted from their current responsibilities to help manage the expansion of the management team. These costs are higher for faster growing firms. Firms, therefore, tend to smooth out their growth paths over time. Additionally, each firm is born with or develops over time certain organizational capabilities and competencies which define what the firm is capable of doing and produce a path dependence of the firm's development (Geroski, 1999). Both arguments lead to a serial correlation of growth rates over time, which is not compatible with Gibrat's Law.

As far as the age of a firm is concerned, learn-theoretic models as proposed by Jovanovic (1982) postulate a negative relationship with firm growth. Older firms have already learned about their relative efficiency and have adapted their size accordingly – they have no need to grow. Moreover, returns from the process of learning are supposed to decrease over time, making it more and more difficult to enhance efficiency further as firms grow older. Life-cycle models explain the negative relationship by increasing saturation of the market for a firm's products (Markusen et al., 1986) and the expanding presence of competitors offering new or enhanced products (Fritsch, 1990).

There is a large body of empirical literature investigating the effects of firm size and age on corporate growth and survival. Size and age are used as control variables in virtually every study on firm performance. Empirical work focusing on start-ups mostly finds that size and age are positively related to likelihood of survival, while growth rates decrease with size and age. Thus, results correspond to Jovanovic's model and contradict Gibrat's Law. According to Geroski's (1995) survey article on market entry, this "stylized result" holds independent of the country, time period, and methodology employed. Confirmations have since been made by Audretsch and Mahmood (1994) for US manufacturing, by Mata (1994) for Portuguese manufacturing, by Almus and Nerlinger (2000) for German start-ups, and by Honjo (2004) for Japanese manufacturing. Mata (1994) and Goddard et al. (2002) illustrate the impact the particular econometric method applied has on the estimated coefficient of firm size. Mata finds evidence of unobserved, time-invariant, firm-specific effects which are positively correlated with firm size and growth. Accounting for these effects by using panel-data methods reveals an even more pronounced negative influence of firm size on growth compared to when standard cross-sectional methods are applied.

However, there is some evidence that, for firms exceeding a certain size (Becchetti and Trovato, 2002) and for those in specific sectors of the economy (Audretsch et al. 1999; Almus, 2002), growth and size are independent of one another. Lotti et al. (2001, 2003) observe a negative effect of size on growth for firms in the Italian manufacturing and instruments industry immediately following start-up. But entrants converge to random growth rates in subsequent years as they attain the MES level of output. Empirical work on the effect of age does not unanimously confirm the stylized result, either. Studies which analyze firms in infant industries or very young firms often show a positive impact of age on growth that diminishes with age (Das, 1995; Almus and Nerlinger, 1999). This suggests that the returns on learning increase at a diminishing rate during the early life-cycle stage of an industry or firm before starting to decrease as the firm or industry matures.

2.2 The Effect of Innovation Activities

The direction of the effect of innovation on employment at the firm level is theoretically ambiguous. In addition to direct effects, indirect effects depending on parameters of the production function, the respective output and labor markets and the characteristics of the innovation itself exist (Blechinger et al., 1998). Innovations can be categorized as process or product innovations. Process innovations make it possible to produce a given amount of output with less input and change the production function of the firm. They are of the labor (capital) augmenting type if they allow reduction of labor (capital) input. Product innovations comprise quality-improved products as well as new products and are supposed to affect the demand function a firm is facing.

The direct effects of process innovations involve an increase in productivity and a decrease in production costs. For a given amount of output, labor-augmenting progress will have a negative impact on employment (displacement effect). However, the decline in marginal costs tends to reduce prices and, thus, increase demand and employment (compensation effect). This indirect positive effect on employment will outweigh the direct negative effect, ceteris paribus, if demand is elastic. Furthermore, it depends positively on the elasticity of substitution between labor and capital (i.e., the degree to which the firm can substitute capital by the relatively more cost-efficient factor labor in the case of the labor-augmenting progress), on the extent of scale economies resulting from the innovation, and on the level of competition and the corresponding degree to which cost reductions are transmitted into price reductions (Van Reenen, 1997; Blechinger et al., 1998).

The direct effect of product innovations is the generation of new demand and/or the conquest of market shares at the expense of other firms. Consequently, firms' employment demand will rise. By offering a new or quality-improved product, a firm can obtain temporary monopolistic profits until other firms are able to imitate the product or develop an even better one. However, the new product might replace existing products offered by the firm. Moreover, the novelty and uniqueness of the product might lead to a lower price elasticity of demand for the product, which entails an increase in price and a decrease in optimal output. As a consequence, the employment of the firm in question might decline (Smolny, 1998b).

The net effect of product innovations on employment depends on the relative strength of these effects. However, the positive quantity effect is more likely to prevail. In the extreme case in which specialized buyers have not previously bought the industry innovator's product, the increase in demand and output can be enormous. There is no similar effect for process innovations (Cohen and Klepper, 1996). Katsoulacos (1986) uses a theoretical analysis to derive a positive net effect of product innovations on employment; conversely, he finds the net effect of process innovations to be negative. Following these results, a negative relation between employment growth and industry age arises. In the early stages of the industry life-cycle, product innovations (i.e, the introduction of new products and further substantial product enhancements) prevail. In later stages in which the product is already largely standardized, process innovations become more important. This would imply that innovations have a positive employment effect in the early stages and a negative effect in the later stages of the industry life-cycle.

Empirical work on the effect of innovations on employment growth has yielded very mixed results. Katsoulacos' (1986) hypothesis that product innovations stimulate employment and process innovations are labor-saving has only been partly confirmed. Many studies detect a positive effect of product innovations and a negative (but often insignificant) effect of process innovations (e.g., Rottmann and Ruschinski, 1997, and Blechinger and Pfeiffer, 1999 for German manufacturing; Brouwer et al., 1993 for Dutch manufacturing; Evangelista and Savona, 2003 for Italian services). Smolny's (1998b) analysis of Western German manufacturing firms reveals a positive effect for both kinds of innovations, but the evidence for the effect of process innovations is rather weak. Blechinger and Pfeiffer find a positive effect of product innovations only for large firms, whereas this effect is negative for some SMEs. Therefore, they caution against deriving any empirical patterns from their results. Similarly, Leo and Steiner (1995) conclude from their analysis of Austrian manufacturing firms that product innovations can increase employment in some firms and lower it in others, citing a dependence on the character of each new product (complementary or substitutional). Analyzing data from the

Community Innovation Survey (CIS) for several European countries, Blechinger et al. (1998) observe a positive employment effect of R&D commitment in German, Danish, Belgian and Italian manufacturing firms. Given the total amount of R&D, a high share of R&D directed toward process innovations significantly decreases employment in German firms. However, the reverse effect can be found in Luxembourg and Italy. Further evidence in favor of a positive effect of process innovations on employment growth is presented by Doms et al. (1994) for US manufacturing plants and by Klomp and Van Leeuwen (2001) for Dutch firms, most of which were involved in the manufacturing sector at the time. Surprisingly, Klomp and Van Leeuwen simultaneously detect a negative effect of the share of innovative products on employment growth. Recent studies by Jaumandreu (2003) and Peters (2004) using CIS data on Spanish and German manufacturing and service firms, respectively, find that product innovations increase employment growth and that the magnitude of the effect corresponds approximately to the increase in innovative sales. In addition, Peters' results reveal that this holds for firm novelties as much as for market novelties. As far as process innovations are concerned, Jaumandreu does not observe any significant negative impact with respect to employment. Peters can only detect such an effect for manufacturing firms which have carried out only process innovations and have introduced a new production technology for rationalization reasons (and not in order to improve product quality or fulfill legal requirements). She argues that the varying effects of different types of process innovations may explain the contradicting empirical evidence concerning the effect of process innovations on employment growth.

Of the studies cited above, those by Das (1995), Goddard et al. (2002), Mata (1994) and Rottmann and Ruschinski (1997) apply panel-data techniques (fixed-effects or random-effects models) based on annual growth rates; Smolny performs pooled OLS regressions. All of the other studies use cross-sectional methods and calculated growth rates for the most part over several years in order to avoid short-term fluctuations. There are only two studies known to the author which – like this analysis – use patents as an innovation indicator and apply panel-data techniques in their analysis of employment growth at the firm level. Van Reenen (1997) uses Arellano and Bond's first-differencing model for UK manufacturing firm data and finds a positive relationship between number of successful innovations[1] and level of employment two or three periods later; the effect of product innovations is stronger than that of process innovations. The number of patents taken out in the US, however, has a positive but insignificant effect when number of innovations is controlled for. Using a fixed-effects model, Greenalgh et al. (2001) discover that R&D intensity as well as UK patent publications have a positive impact on employment level in British industrial and commercial companies. Instead

1 "Successful innovation" here means the successful commercial introduction of new or improved products or processes.

of patent counts, they use a weighted average of patents published between two and four years prior to the employment observation, with weights reflecting the average rate of patent renewals. Like Van Reenen (1997), they are unable to find a positive impact of US patents on employment and conclude that patents in the respective domestic market, rather than US patents, have a significant value to UK firms.

Only little empirical work on the effect of innovative activity on the post-entry performance of start-ups exists. Some studies compare the growth chances of young firms in high-tech and low-tech industries without considering the innovative behavior of the individual firm. They all find the growth rates of start-ups to be higher in technology-intensive sectors of the economy (Kirchhoff and Phillips, 1989; Almus and Nerlinger, 1999; Audretsch, 1995). Tether (1997) derives some stylized facts regarding mean employment creation in innovative and technology-based new and small firms: Controlling for size and age, innovative and technology-based firms significantly outperform firms from the general population in terms of rate of job creation, but the mean rates of direct employment creation in these firms are only modest. Moreover, the distribution of the rates of job creation is highly skewed, i.e., the bulk of jobs are created by a small subset of the total population of innovative and technology-based new and small firms.

There is hardly any empirical literature, however, on the effect of innovative activities on post-entry performance at the firm level. One exception is a paper by Hsueh and Tu (2004), who use data on a cross-section of new Taiwanese SMEs to investigate the impact of various innovation indicators on sales growth and profit rates. According to their results, the cultivation of an innovative atmosphere and of the capability to innovate enhances both performance measures, especially profits. Sales growth is more strongly fostered by innovative actions like R&D, process innovations, moving into new business areas and using new marketing channels.

The lack of empirical research on the effects innovative activity has on the success of entrants is surprising. It is widely recognized that new firms play a decisive role in the innovation process. Start-ups are often founded in order to introduce new innovations into the market. It is also well known that innovations attract imitators, causing the competitive advantage emanating from an innovation to disappear in the long run. In order to be successful in the market, start-ups have to constantly implement innovations. The contribution of this paper is its investigation of the impact of innovative behavior on post-entry performance over the first years of firms' life-cycles. Employment growth is used as a performance measure, and patent applications are utilized as an indicator of innovation.

3. Methodological Issues

There are several methodological problems associated with the empirical analysis of how innovative activity affects employment growth. Firstly, the evolution of employment size is determined by many factors. All of these have to be controlled for in order to isolate the specific contribution of a certain variable. However, not all the determinant factors are observed – there is unobserved heterogeneity. If these unobserved effects are correlated with the observed explanatory variables in the model, the estimated coefficients will be biased. For example, innovative firms often have unobserved comparative advantages in implementing new technologies or possess special strategic competencies. If employment growth in these firms is driven by these unobserved factors, the effect of innovation per se will be overestimated unless one controls for unobserved heterogeneity. Panel-data models accounting for unobserved, time-constant individual effects may help to overcome this problem.

Secondly, the data set used might be a non-random sample of the whole population of firms, allowing the estimation to be affected by selection bias. With panel data, this problem becomes aggravated in the presence of panel attrition, i.e., if some firms drop out of the panel after a period of time. If the selection mechanism is non-random but systematically related to the response variable after conditioning on explanatory variables, the estimated coefficients might be biased. In the present case, in which only surviving firms enter the estimation procedure, such a systematic relation is very likely to exist because the growth and survival of firms can be supposed to be partially influenced by the same unobserved factors. If these unobserved factors are correlated with those observed, failure to control for them will lead to erroneous inference regarding the impact of the observables on the dependent variable. For example, it has been claimed that the negative relationship between size and growth revealed by many empirical studies is actually due to failing to account for survival bias (Mansfield, 1962). Unobserved factors correlated with small firm size influence survival as well as growth negatively. The early exit of small firms with minor growth rates leads to an overly positive picture of small firms′ growth performance and a false rejection of Gibrat′s Law. As long as the probability of being in the sample is constant over time, consistent estimates can be obtained from fixed-effects or first-differencing panel-data methods. However, if selection varies over time and is correlated with the error term of the structural equation of interest, special methods correcting for selection bias have to be applied.

Further attention should be devoted to the possible endogeneity of innovative activity as a determinant of employment growth. If the innovation indicators themselves are affected by growth, econometric methods allowing for endogenous explanatory variables have to be used. Generally, one might expect a two-way relationship between R&D, innovation activities and performance at the firm level: A firm's innovativeness is an important determinant of its performance in the subsequent period, but its current performance may also control its future innovative effort. This is plausible for performance measures such as cash flow or sales, which are closely connected to the liquidity of a firm and, thereby, determine its ability to finance innovation activities. It may also apply to employment growth, which can be considered as a proxy for the demand expectations of a firm. In order to capture a greater part of the growing market, a firm might decide to undertake innovative efforts. However, firms can directly influence only the inputs into the innovation process. Throughput and output indicators (patents, innovations) cannot be planned exactly since they involve R&D efforts with long gestation periods and uncertain success (Van Reenen, 1997). A priori, it is not clear whether one can assume innovations to be predetermined or must consider them as endogenous with respect to employment growth. In their specification of an empirical model based on the innovation model of Kline and Rosenberg (1986), Klomp and Van Leeuwen (2001) preclude any influence of employment growth on innovation by allowing for a feedback loop proceeding only from sales growth to innovation output. There is no study known to the author which documents the effect of employment growth effect on innovations. Performing a Granger causality test, Lööf and Heshmati (2004) cannot detect any significant impact of employment growth on R&D intensity.

Another problem is presented by the appropriate measurement of employment and innovation activity. Regarding employment, simply using number of employees might be misleading. Firstly, if labor-saving progress, for example, is implemented by a reduction of hours worked instead of a reduction of number of employees, the effect of technical progress on employment will be underestimated (Blechinger et al., 1998). Hence, it is preferable to use number of hours worked. Secondly, innovations may affect various skill levels of employment very differently. There is usually a complementarity between new technology and skilled labor; this causes the demand for skilled labor to rise with technical progress while the demand for unskilled labor declines (Blechinger et al., 1998). It is therefore desirable to have employment data distinguishing the skills required to do each individual job. Unfortunately, no information on hours worked or skills was available for this study.

Different indicators have been used to measure innovative activity. There are input-oriented indicators like share of R&D personnel in total personnel or R&D expenditures per employee, as well as output-oriented measures such as innovation counts, self-reported statements on innovations or share of turnover attributable to innovations. Measures also exist which have been referred to as an intermediate result of the production process or a throughput indicator of innovation (Licht and Zoz, 1996; Blechinger et al., 1998), namely number of patent applications or grants. On the one hand, patents are inventions and insofar the output of research activity. A patent application indicates that R&D efforts have been productive and have led to an invention which the enterprise considers to be worth protecting. On the other hand, patents have to be combined with information on manufacturability and user needs in order to be implemented in the production process or converted into a marketable product. They can, thus, be seen as an input factor for innovations which at the same time enable firms to exert property rights and appropriate profits from their ideas.

Of these measures, the one most suitable for empirical analysis depends on the research topic. If the effect of innovative activity on employment is to be analyzed, output-oriented indicators incorporating economic success - and thus the respective demand situation - should be preferred, since a firm's employment decision depends heavily on demand (Blechinger et al., 1998). In this study, such indicators were not available for the underlying data set. For patents (which have been used instead) the link to economic success is not as strong. Like all input and throughput indicators of innovation, they affect productivity and output after a delay. The underlying inventions first have to be converted into new production techniques or marketable products. New capital equipment, training or even further R&D might be necessary. Moreover, patents can be regarded as real options guaranteeing exclusive rights which allow firms to hold off on the conversion into innovations. When facing uncertain market conditions, firms might prefer to delay these investments, which are at least partly irreversible (Bloom and van Reenen, 2002). Hence, the length of time before patents affect firm performance depends on the quantity and quality of the necessary investments and on market conditions.

Furthermore, the patent indicator is beset with three fundamental problems: First, not all inventions are patentable; second, not all patentable inventions are patented; and third, patented inventions differ greatly in quality (Griliches, 1990). As to the first point, there are some kinds of technical progress, e.g., imitative or incremental innovations, which are too small or too applied in nature to be patentable. Still, they represent an increasingly important part of innovative activity and may affect firm performance (Licht and Zoz, 1996). Referring to the second point, it is clear that patents are only one way of protecting an innovation and not always the most effective one. In some cases, other mechanisms like secrecy, lead time or long-term employment contracts are better suited to appropriate returns on R&D. Patents disclose at least some information to competitors via patent documents and can play an important role in information diffusion (Cohen et al., 2002). The inclination to use patents for innovation protection is supposed to depend on the industry and type of innovation involved. Patents are a more efficient protection mechanism for product than for process innovations (König and Licht, 1995). For process innovations, secrecy is a more effective instrument of avoiding imitation. The last point refers to the fact that some patents reflect important inventions leading to successful innovations, while others have almost no economic significance and are not converted into innovations. Accordingly, some patents improve firm performance and others do not. This makes it difficult to estimate the average effect precisely.

Finally, it is not likely that the effect of innovative activity – no matter how it is measured – will be restricted to one time interval. It is likely distributed over several delays, as it takes some time for a firm to fully adapt its production to the new technique/product in question. This makes it difficult to estimate the overall impact of innovation. Furthermore, only the effects of the proceeds of innovating (involving either a product or process) have been addressed thus far. However, the process of innovating will increase a firm's ability to appropriate knowledge contained in other firms' innovations and will improve its general competitiveness. Therefore, innovating firms can be assumed to perform generally better than their non-innovating counterparts (Geroski et al., 1993).

4. Econometric Model

The empirical analysis is based on a model which has commonly been used as a starting point for testing Gibrat's Law:

$$y_{it} - y_{i,t-1} = \alpha_i + \beta y_{i,t-1} + u_{it}; \qquad u_{it} = \rho u_{i,t-1} + e_{it}.$$

The dependent variable is the logarithmic employment growth rate with y_{it} being the logarithm of employment of firm i in period t. u_{it} is an error term. β determines the relationship between logarithmic firm size and logarithmic firm growth. $\beta=0$ implies that employment grows independently of firm size, the case described by Gibrat's Law. Further, if $\rho = 0$, growth follows a random walk, which is another implication of the law. Departures from the law arise if either $\beta \neq 0$ (with $\beta > 0$ implying explosive growth rates, and $\beta < 0$ implying mean-reverting firm sizes) or $\rho \neq 0$ (with $\rho > 0$ implying that above-average growth tends to persist, whereas for $\rho < 0$ such growth tends to be followed by below-average growth).

Equation 1 is estimated using fixed-effects and first-differencing methods. According to a reparameterization of the model suggested by Goddard et al. (2002)[2], lagged employment growth is included as an additional regressor. Moreover, following Evans (1987a,b), the logarithm of firm age and the second-order expansion of logarithmic size and age are added. Legal form and indicators of current and past patenting activity are included, as well. While the fixed-effects model assumes the error term u_{it} to be homoscedastic and serially uncorrelated, the first-differencing model implies that u_{it} follows a random walk (Wooldridge, 2002). The relative efficiency of the fixed-effects and first-differencing methods depends on the appropriateness of their assumption concerning the time-series properties of u_{it}. In addition to the standard within

2 Goddard derives the following reparameterization:
$y_{it} - y_{i,t-1} = \alpha_i(1-\rho) + \beta y_{i,t-1} + \rho(y_{i,t-1} - y_{i,t-2}) + \eta_{it}$ with $\eta_{it} = e_{it} + \rho\beta y_{i,t-2}$.

estimator, a fixed-effects model where the error term u_{it} is assumed to follow a first-order autoregressive process is estimated. The first-differencing model is estimated by 2SLS using lagged values of $y_{i,t-1}$ as instruments for the lagged dependent variable on the right-hand side. The first-differencing method is more appropriate than the fixed-effects approach if no exogenous instruments are available, as in this case (Wooldridge, 2002). Nevertheless, according to Goddard et al. (2002), the fixed-effects model is adequate to test Gibrat's Law and is in any case preferable to cross-sectional tests due to its important advantage of accounting for heterogeneity. It will therefore be used as a standard of reference in this study.

The first-differencing model is also appropriate for coping with the possible non-randomness of the sample. Selection bias could be caused by the temporary (incidental truncation) or permanent drop-out (attrition) of units observed in the data. The permanent drop-outs are often due to firm closure, which, as stated above, should be influenced by the same unobserved factors as growth. However, firms dropping out for other reasons may also exhibit unobserved characteristics affecting employment growth. In order to eliminate attrition bias, an extension of Heckman's (1979) two-step selection correction procedure to the panel-data context as described in Wooldridge (2002) is used.[3]

5. Description of Data

The empirical analysis is based on a sample of German firms founded between 1990 and 1993. The impetus behind the creation of this data set was to research the foundation activities and post-entry performance of Eastern and Western German firms immediately following German reunification. For the configuration of the sample, a stratified sample of 12,000 firms was drawn from the ZEW Foundation Panels, two complementary firm panels maintained by the Centre for European Economic Research (ZEW), Mannheim (see Almus et al., 2000 for details). The firm data were provided by Creditreform, the largest credit agency in Germany, which collects information on

3 Let S_{it} denote a selection indicator where $S_{it}=1$ if firm i is observed in t and $S_{it}=0$ if it is missing due to permanent drop-out. S_{it} is only set to zero in the period immediately following a unit's departure from the sample. In later periods, these units will be ignored. The first step consists of a probit estimation of the selection equation

$$s_{it} = 1(w_{it}\delta_t + v_{it} > 0), \qquad v_{it}\left|\{w_{it}, s_{i,t-1} = 1\}\right.\sim\text{Normal}(0,1)$$

for each $t\geq 2$. w_{it} should contain all regressors of the structural equation to avoid exclusion restrictions on a reduced-form equation. Moreover, it should include at least one significant explanatory variable which is not part of the structural equation. Inverse Mills ratios $\hat{\lambda}_{it}$ are calculated for each of the T-1 probit estimations. In the second step, these are included in Equation 1, yielding $y_{it} - y_{i,t-1} = \alpha_i + \beta y_{i,t-1} + \rho_2 d2_t\hat{\lambda}_{it} + \ldots + \rho_T dT_t\hat{\lambda}_{it} + u_{it}$
where $d2_t$ through dT_t are time dummies. Attrition bias can be tested by a joint test of $H_0{:}\rho_t=0$ for $t=2,\ldots,T$.

active, legally independent firms. The data contain information on variables like industry, legal status, foundation date, region, and founding parties' human capital. They comprise virtually all Eastern and Western German firms found in the trade register. The probability of unregistered firms entering the panel depends on the scope of their credit demand and of their business relationships with other firms.

The sample drawn from the foundation panels is stratified by region: It consists of two pools of 6,000 firms each from Eastern and Western Germany, respectively. An indicator demonstrating whether each firm had possibly exited the market was applied as a further stratification criterion. Such firms were over sampled in order to counterbalance the probable positive selection encountered in enterprise panels, which results from the difficulty of contacting agents of non-surviving firms and from their unwillingness to report failure. The sample is confined to firms founded between 1990 and 1997 (more than 90 percent were founded between 1990 and 1993) in the manufacturing, construction, trade, transport and communication, and service sectors. A large telephone survey conducted in 1999 and 2000 provided information not contained in the foundation panels, e.g., annual number of employees and exact date of firm closure. The survey ended up with 3,702 successfully interviewed firms.[4] For the larger part of this study's analysis, legally dependent firms, firms which were not truly new foundations but takeovers, those that submitted a foundation year earlier than 1990 in the telephone interview, and those belonging to sectors of the economy in which patents have no relevance (transport and communication, retail trade, and consumption-related services)[5] have not been included. Furthermore, firms with an average employee base of more than 500 employees and firms for which no employment figures were obtained have been excluded. Firms with implausibly high average growth rates have also been dropped. In the end, 1,387 firms remain for the analysis. Annual growth rates can be calculated from the foundation year up until 1999 or the respective year of closure.

5.1 Comparison of Eastern and Western German Firms

Table 7.1 contains some descriptive results for the start-up firms, differentiated by region. It shows that 60 percent of the firms in the sample are situated in Eastern Germany. This disproportionately large share stems from the Eastern German firms' higher rate of response to the survey. This in turn can be explained by a certain surfeit of surveys in the West which is not yet that prevalent in the East. The distribution by sector reveals an above average share of construction start-ups in Eastern Germany. It reflects the (govern-

4 The survey is called „ZEW-Gründerstudie“ and is described in detail in Almus et al. (2001).

5 In the communication/transporting and consumption-related service sectors, not a single patent was applied for during the observation period; in the retail trade sector only one patent application was filed.

ment-subsidized) boom which resulted from the immense need for reconstruction and development of buildings after the German reunification. There are comparatively few foundations in business-related services in the East, indicating that the traditional economic structure characterized by a strong industry sector still prevails. The transition to a more service-oriented modern economy has taken place rather slowly. One reason for this might be the lack of highly qualified people particularly vital to this branch.

Table 7.1: Descriptive statistics for Eastern and Western German firms

	All Firms	Eastern German firms	Western German firms
Number of firms	1,387	832 (60.0%)	555 (40.0%)
Firms by sector (%)			
manufacturing	*22.4*	*22.5*	*22.3*
construction	34.5	41.9	23.2***
wholesale & intermediate trade	19.0	16.6	22.5***
business-related services	24.2	19.0	31.9***
Mean annual growth rate	12.7	14.3	10.4**
Surviving firms (%)	73.3	74.0	72.1
Mean employment size	16.6	21.1	9.8***
Average capital at foundation (DM)	706,117	1003,890	271,778
Average owner capital at foundation (DM)	150,658	153,909	145,889
Public start-up assistance (%)	32.3	41.0	16.6***
Firms by earliest legal form (%)[6]			
ltd. liability company	58.0	55.3	62.0**
civil law association	10.6	10.7	10.5
commercial partnership	1.4	1.6	1.3
sole proprietorship	29.9	32.2	26.3**
Founder education, highest level (%)			
doctorate	2.9	2.4	3.8
other academic degree	30.3	33.1	26.1***
master craftsman	15.8	15.6	16.0
apprenticeship	26.2	18.5	37.7***
low education	0.8	0.6	1.1
education unknown	24.0	29.8	15.3***
Year of foundation (%)			
1990	26.7	26.7	26.8
1991	24.4	25.5	22.9
1992	21.8	23.0	20.0
1993	19.2	17.2	22.2**
after 1993	7.9	7.6	8.3

*** (**,*) indicates a significance level of 1% (5%, 10%) in a two-tailed t-test on the equality of means.

6 The legal form of the remaining non-patenting firms is unknown. There are no stock companies in the sample.

Eastern German firms exhibit significantly higher employment growth rates than Western German firms. This reflects the higher growth potential of a transition economy as compared to an established market economy. Eastern German firms are about twice as large on average as their Western German counterparts and dispose of almost four times as much capital during foundation. This has to be seen in the context of a substantially higher share of Eastern German firms receiving public start-up assistance and more favorable conditions of East-oriented financing programs, indicating that federal subsidization policies after reunification concentrated mainly on Eastern Germany.[7] The average size of loans given to Eastern German start-ups dwarfs that of Western German firm foundations by 90 percent. The larger average employment size of Eastern German firms is somehow contradictory to their comparatively high share of sole-proprietorship firms. However, this can partly be explained by the fact that the response rate of start-ups founded in this legal form is not as disproportionately low for Eastern German firms as for those in Western Germany (Almus et al., 2001).

The distribution by education indicates that Eastern German founders are more highly educated than firm founders in the West. However, this result has to be interpreted with caution since the degrees of educational attainment in Western Germany and the former German Democratic Republic are not directly comparable. The high non-response rate of Eastern German firms to this question might reflect an awareness of this incongruity.

Finally, the table indicates that foundation rates were largest immediately after the collapse of the German Democratic Republic and constantly declined in Eastern Germany from 1990 on. The early start-up cohorts were probably able to realize first-mover advantages from reacting quickly to the changing political and economic conditions. A similar pattern can be observed in Western Germany, where firms benefited from the reunification-related boom. It should be noted, however, that the response rate of the 1990 cohort was slightly higher than that of the 1993 cohort (Almus et al., 2001).

5.2 Comparison of Patenting and Non-Patenting Firms

The firm data set has been merged with German patent data by a text field analysis of the firm names. Each attribution of a patent to a firm made by the software program was checked by hand by comparing the exact names and addresses of both data sets. The data basis of the following analysis can therefore be considered reliable.

The patent data contain information on patent number, year of application, IPC code, an indicator of whether the application was made at the European Patent Office (EPO), year of acceptance, and number of citations. The combi-

7 The information on receipt of start-up assistance was obtained from the former *Deutsche Ausgleichsbank (DtA),* the second largest public bank in Germany. For a detailed description of the start-up assistance programs see Prantl (2002).

nation of the two data sets allows an analysis of the relation between innovative activity and employment growth. In the following, some descriptive findings from examinations of the merged data set are depicted.

Only 44 (3.2 percent) of the 1,357 firms applied for one or more patents between 1990 and 1999 (see table 7.2). All told, the sampled firms made 128 patent applications in that period, 21 (16.4 percent) of which were applied for at the EPO and 56 (43.8 percent) of which were granted up to the year 2003.[8] The distribution by economic sector reveals that half of the patent applications come from the manufacturing sector. This explains why the empirical literature concerning patents has focused primarily on this sector. There is, however, considerable patenting activity in business-related services as well; over a third of all patents stem from this sector. The rest come from the wholesale and intermediate trade sector and – to a very small extent – from construction.

As a comparison with the sectoral distribution of patenting firms shows, the sectors obviously differ by their mean numbers of applied-for patents. The share of manufacturing firms in patenting firms is somewhat higher than that of manufacturing-related patent applications in all applications: The mean number of applications by patenting firm is, hence, lower than average in manufacturing. In contrast, the share of business-related service firms in patenting firms is smaller than the share of applications attributable to this sector in all applications. Consequently, the mean number of patent applications per patenting firm is higher than average in business-related services. The share of patent applications from both manufacturing and business-related services far exceeds the weight of these sectors – as measured by the number of firms found in each – in the economy. The opposite holds for wholesale and intermediate trade and, in particular, construction. Overall, the distribution of patent applications across patenting firms is highly skewed. 43 percent of all patenting firms only applied for one patent within the given period; a quarter of them applied for two patents. However, only about 5 percent of the patenting firms applied for more than ten patents, thereby accounting for more than a quarter of the total number of patent applications.

Average annual employment growth rates apparently do not significantly differ between patenting and non-patenting firms. This result contrasts with one of the stylized facts found by Tether (1997), according to which innovative firms outperform other firms in terms of job creation. Even taking into account that patenting behavior is not a perfect indicator of innovativeness, this difference is striking. Further analysis shows that the share of firms exhibiting growth rates near the outer edge of the distribution is higher among patenting than among non-patenting firms. Patenting firms more often evince growth rates above the sample's upper quartile, but also exhibit declining em-

8 The relatively low percentage of granted patents may be due to the fact that the patent data are still incomplete for the year 2000 and after. The fraction of granted patents may, therefore, be underestimated for patent applications from the late 1990s.

ployment more often than their non-patenting counterparts. For the latter, growth rates close to zero are observed more often.

Table 7.2 further indicates that patenting firms have a higher probability of survival than their non-patenting counterparts. However, the difference is only slightly significant. Average employment size (the average of the annual employment figures available for each firm) is more than twice as large for patenting firms as for non-patenting ones. The amount of seed capital utilized by patenting firms is several times larger than that disposed of by non-patenting start-ups. Half of the patenting firms received start-up assistance compared to only a third of the non-patenting companies, and the average loan size of the former group is three times larger. This reflects a "picking the winner" strategy of capital lenders, who obviously consider innovative firms to have higher chances of success.

The mean age of patenting firms at the time of patent application is slightly lower than their mean age over the observation period, suggesting that firms rather exhibit patenting activity at a relatively early stage in the life cycle. Patenting firms are mostly founded in the legal form of limited liability companies, something which is less common among non-patenting firms; the latter are more often sole proprietorships. Firms engaging in patent activity are more often situated in the western part of Germany than non-patenting firms. Comparing firm founders' highest level of education shows that founders of patenting firms possess doctorate degrees more often than those of non-patenting companies. Somewhat surprisingly, they do not have other academic degrees more often.

Finally, the distribution of patenting firms across federal states is depicted in table 7.3 and is compared to the distribution of all firms. The table refers to the complete sample of successfully interviewed firms (n=3702) and displays the distribution separately for Eastern and Western Germany. Otherwise, the results would be heavily biased because of the higher response rate of Eastern German start-ups.

In Western Germany, most patenting start-ups are situated in North Rhine-Westphalia and Bavaria. This cannot just be explained by the large size of these states because their share in patenting start-ups surmounts their share in all start-ups; in other words, the share of start-ups exhibiting patenting activity in all start-ups in these states is higher than in other states. Relatively low (or even non-existent) shares of young, patenting firms can be observed in the northern states Schleswig-Holstein, Bremen, Hamburg, Lower Saxony and West Berlin. In Eastern Germany, disproportionately high shares of patenting start-ups are present in Saxony and Thuringia. In contrast, shares are relatively low in Mecklenburg-Western Pomerania and Saxony-Anhalt. In order to compare the innovativeness of Eastern and Western German start-ups, the share of patenting start-ups in all start-ups was calculated for each region. It stands at 2.1 percent in the East and at 2.7 percent in the West. It is higher in several Eastern states than in some Western states.

Table 7.2: Descriptive statistics for patenting and non-patenting firms

	All Firms	Non-Patenting Firms	Patenting Firms
Number of firms	1,387	1313 (96.8%)	44 (3.2%)
No. of patent applications	128.0	-	128.0
No. of EPO patent applications	21.0	-	21.0
No. of granted patents	56.0	-	56.0
Patents by sector (%)			
manufacturing	49.2	-	49.2
construction	1.5	-	1.5
wholesale & intermediate trade	12.9	-	12.9
business-related services	36.4	-	36.4
Firms by sector (%)			
manufacturing	22.4	21.2	59.1***
construction	34.5	35.5	4.6***
wholesale & intermediate trade	19.0	19.1	13.6
business-related services	24.2	24.2	22.7
Mean annual growth rate	12.7	12.7	11.8
Surviving firms (%)	73.3	72.9	84.1*
Mean employment size	16.6	15.9	37.9***
Average capital at foundation (DM)	706,117	403,945	8897,432***
Average owner capital at foundation (DM)	150,658	138,995	487,571**
Public start-up assistance (%)	32.3	31.9	48.8**
Mean firm age	3.3	3.3	3.5
Mean firm age at patent application	-	-	3.0
Firms by earliest legal form (%)[9]			
Ltd. liability company	58.0	57.3	79.6***
Civil law association	10.6	10.7	6.8
Commercial partnership	1.4	1.5	0.0
Sole proprietorship	29.9	30.4	13.6**
Western Germany (%)	40.0	39.6	52.3*
Founder education, highest level (%)			
doctorate	2.9	2.8	9.1**
other academic degree	30.3	30.3	29.6
master craftsman	15.8	15.9	13.6
apprenticeship	26.2	26.1	27.3
low education	0.8	0.8	0.0
education unknown	24.0	24.1	20.4

*** (**,*) indicates a significance level of 1% (5%, 10%) in a two-tailed t-test on the equality of means.

9 The legal form of the remaining non-patenting firms is unknown. There are no stock companies in the sample.

Table 7.3: Distribution of (patenting) start-ups across Federal States (%)

	Patenting start-ups	All start-ups	Share of patenting start-ups in all start-ups
Schleswig-Holstein	2.2	3.5	1.7
Hamburg	0.0	1.6	0.0
Lower Saxony	6.7	10.3	1.7
Bremen	0.0	0.8	0.0
North Rhine-Westphalia	37.8	30.0	3.4
Hesse	4.4	9.7	1.2
Rhineland-Palatinate	2.2	5.5	1.1
Baden-Wuerttemberg	13.3	14.0	2.6
Bavaria	31.1	20.3	4.1
Saarland	2.2	2.2	2.7
Berlin (West)	0.0	2.1	0.0
Total/mean	100	100	2.7
Berlin (East)	2.3	4.1	1.2
Brandenburg	20.9	17.6	2.5
Mecklenburg-Western Pomerania	2.3	12.4	0.4
Saxony	41.9	29.8	3.0
Saxony-Anhalt	7.0	16.1	0.9
Thuringia	25.6	20.0	2.7
Total/mean	100.0	100.0	2.1

These numbers do not correspond to official patent statistics concerning general patenting intensity in Germany's federal states. According to these statistics (Greif und Schmiedl, 2002), number of patent applications per employee is largest in Baden-Wurttemberg, Bavaria, and Hesse. This figure is always higher for Western states. Thus, it can be concluded that the regional distribution of patenting intensity differs between established and start-up firms. In particular, while patenting activity in the East is substantially lower than in the West in general, it is only slightly lower in start-ups.

6. Empirical Results

The econometric analysis incorporates the estimation of an employment growth equation using fixed-effects as well as first-differencing methods. The names and definitions of the explanatory variables are given in table 7.4. The analysis is based on an extended version of Equation 1 as described above. Patenting activity is measured by a variable indicating whether each firm applied for any patents during the year of observation, by number of patent applications, or by patent stock. The first two indicators are included with two lags in order to account for the delay with which patenting behavior may affect employment. The patent stock is a weighted index of the number of current-period and past patent applications. It is based on a standard perpetual-inventory equation with constant depreciation:

$$pat\_stock_{it} = (1-\delta)pat\_stock_{i,t-1} + numb\_pat_t ,$$

where the depreciation rate δ is chosen to be 15 percent (Griliches and Mairesse, 1984; Czarnitzki and Kraft, 2004). Thus, the older the patent application the smaller the weight attributed to it in the patent stock. On the one hand, the use of a patent stock measure has the advantage of avoiding the problem of long lag structures. The coefficients of the other patent indicators' different lags may be estimated somewhat imprecisely because of the correlation of a firm's patenting behavior over time. On the other hand, the patent stock measure presumes a specific lag structure and does not allow the relative impacts of different lags to vary. An interaction term involving patent stock and age is included to test whether the effect of patenting activity varies over each firm's life cycle. The patenting indicators are not instrumented, as they turn out to be exogenous in Granger causality tests. The test's conclusion corresponds to the theoretical modeling and empirical evidence concerning employment growth and innovative activity as cited in the methodological section.

Table 7.4: Variable definitions

Variable name	Variable description
Δ employment	logarithmic employment growth
employment	log of employment
age	log of firm age
empl*age	interaction between log of employment and log of firm age
ltd_ liability	limited liability company
numb_pat	number of patent applications in current period
patent	indicator taking value 1 if firm applied for at least one patent in current period, 0 otherwise
pat_stock	weighted index of number of current and past patent applications
pat_stock*age	interaction between patent stock and log of firm age
attr_dead	leading selection indicator taking value 1 if firm leaves the panel due to firm closure in subsequent period, 0 otherwise
attr_perm	leading selection indicator taking value 1 if firm leaves the panel permanently for reasons other than closure in subsequent period, 0 otherwise
att_temp	leading selection indicator taking value 1 if firm leaves the panel temporarily in subsequent period, 0 otherwise
mills 93-99	inverse Mills ratios estimated from probit regressions (equation 5)

In addition, indicator variables of either possible selection bias or selection correction terms are included in the regressions. Three indicators of selection bias specify whether a firm is missing in the subsequent period because of permanent drop-out due to firm closure, permanent drop-out due to other reasons or temporary drop-out, respectively. Using them in the regression allows only testing for selectivity. In order to correct it, the Heckman procedure is applied and Mills ratios are inserted as correction terms.

Table 7.5 shows the estimation results using four different econometric approaches with employment growth as the dependent variable. The right-hand side variables are displayed in the first column. The second column contains the estimated coefficients of the fixed-effects model. The results in the third column are based upon a fixed-effects model in which the error term is assumed to follow a first-order autoregressive process. The 2SLS results of the first-differencing model without selection correction using lagged values of $y_{i,t-1}$ as instruments are given in the fourth column. The last column shows the corresponding 2SLS results with selection correction.[10]

The outstanding difference between the fixed-effects models with and without serial dependence in the disturbances is the direction of the effect of employment growth, lagged by one period. While this effect is positive in the normal fixed-effects model, it is negative in the fixed-effects model allowing for autocorrelated disturbances. This could be explained as follows: Even when controlling for time-constant, firm-specific effects, individual growth rates are positively correlated over time. This correlation might be due to firms smoothing out their growth rates over time - as suggested by Penrose - to a specific economic situation lasting several periods or to a firm's temporary competitive advantage. When controlling for such effects using autocorrelated errors, the effect of the past growth rate itself is negative, which can be ascribed to oscillatory movements of growth rates measured on an annual basis. Hence, the fixed-effects model with autocorrelated disturbances, which allows differentiation between these opposite effects, is clearly preferable to the normal fixed-effects model. Still, it should be remembered that the inclusion of the lagged dependent variable in a fixed-effects regression leads to estimation bias. In this respect the first-differencing method with which lagged growth and lagged employment size are instrumented by their past values is more reliable; it also allows for serial correlation of the error term in the form of a random walk. The two first-difference estimations in table 7.5 do not reveal any significant effects of past growth on current growth.

However, even if the growth process is not path-dependent, Gibrat's Law can clearly be rejected on the basis of the results in table 7.5: All four estima-

10 Number of observations and number of firms are lower in the fixed-effects model with autocorrelated errors than in the normal fixed-effects model because the maximum number of observations per firm available for estimation is lower in the former. One observation per firm is needed for the estimation of the autocorrelation coefficient which cannot be used for the growth regression. Number of observations is even lower in the first-differencing model because two observations are needed to generate the instruments for the lagged dependent variable.

tions show a highly significant negative effect of previous firm size on current growth, although the positive sign of the quadratic term – which is significant in the first-differencing models – indicates that this negative effect diminishes with size. The turning point at which the negative effect turns positive, however, is much higher than the maximum employment size ever reached by firms in the sample during the observation period. Thus, small firms clearly grow faster than their larger counterparts. Employment growth is not a random process independent of firm size. The fixed-effects models indicate further that the negative effect of firm size on growth becomes more pronounced as firms get older. This can be concluded from the coefficient of the interaction term between size and age. However, this effect is not confirmed by the first-differencing models.

Firm age has a significant positive effect on growth. This result is inconsistent with many empirical studies which find a negative relationship between age and growth; this can be explained by the fact that the present data set contains only start-up firms. The propensity to grow may actually be quite low shortly after firm formation, when a firm has yet to learn about its efficiency relative to its competitors. The more it learns and discovers that it operates efficiently, the more likely it is to decide to stay in the market and grow. In addition, returns on learning might be increasing in such early stages of the life cycle. The results are in line with other studies based on start-up samples which find a positive effect of age on growth that turns negative after a few years (Almus and Nerlinger, 1999; Almus et al., 1999). However, evidence for the existence of a turning point at which the effect becomes negative can only be found in the fixed-effects models.

Legal status affects employment growth as well. Firms with limited liability have significantly higher growth rates in comparison with other companies. This result is in line with other empirical work, such as Harhoff et al., (1998) and Engel (2002).

Patenting activities have a clear, positive impact on employment growth. Firms that apply for patents have above-average growth rates in the subsequent two years. This conclusion can be drawn from the results of the first-differencing models. The model without selection correction indicates a slightly significant positive effect even in the year of application. According to the fixed-effects estimates, a significant impact is only manifest in the second year after application. Both types of model agree that the effect is greatest in that year. This can be explained by the fact that inventions have to be converted into marketable products or implemented into the production process before they can have an impact on employment. More immediate effects might be due to the hiring of personnel in order to facilitate the execution of these tasks. Firms might also be inclined to recruit new employees promptly in order to be able to fully exploit the competitive advantage implied by their patents.

An obvious weakness of the present model specification is its lack of any financial indicators serving as explanatory variables. Patenting activity might just be an indication of available internal financing, an important factor for growth. Unfortunately, there are no time-varying financial variables available for the present data set, only information on whether investment activities are being carried out by external firms. Such investments should provide an indication of firms' financial situations. However, the corresponding variable proves to be insignificant in the estimations.

They only contain the leading selection indicators which allow testing for selectivity. As the results show, firms leaving the panel consistently show a relatively low employment growth rate in the precedent period. As expected and as ascertained by Almus (2002), attrition due to firm closure is preceded by poor growth performance. That this also holds for drop-outs due to other reasons could be ascribed to firms' reluctance to report on the "rough patches" they go through.

Columns 2 - 4 in table 7.5 refer to estimations without selection correction. These findings indicate the presence of an attrition bias. The last column gives the estimation results of a first-differencing model which corrects for this bias. It is not corrected for a possible bias due to temporary drop-out since the existence of such a bias is rejected by the test. The regression includes the inverse Mills ratios from the T – 1 probit estimations of equation 5 (not reported) as instruments in the first stage and as explanatory variables in the second stage.[11] The significance of the coefficients of six of the seven inverse Mills ratios again confirms the presence of attrition bias. Consequently, one would tend to have more confidence in the results of the regression correcting for the bias. However, the estimated coefficients of the two first-difference regressions differ only slightly. This indicates that the leading selection indicators already correct the bulk of the attrition bias.

Table 7.6 shows the estimation results of the fixed-effects model with autocorrelated disturbances and of the first-differencing model without selection correction using two other patenting measures, namely number of patent applications and patent stock. Comparing the results of the second and fourth columns with the corresponding estimations in table 7.5, it turns out that number of patent applications has less influence on growth than the indicator of whether a firm has applied for any patents. Thus, it is rather the act of carrying out patenting activities itself than a firm's number of patent applications which enhances employment growth. Number of applications might be less meaningful due to the varying quality and economic significance of patents.

11 Explanatory variables which are included in the probit but not in the 2SLS regression in order to avoid multicollinearity are founders' human capital, region (Eastern or Western Germany), population density, an indicator of whether each firm had received start-up assistance, and indicators of the payment history of each firm. They all lend significant explanatory power to the selection regressions.

Table 7.5: Fixed-effects and first-difference employment growth regressions I

	FE	FE with AR(1)	FD	FD with selection correction
Δ employment t-1	0.041*** (0.011)	-0.045*** (0.015)	-0.001 (0.025)	-0.031 (0.020)
employment t-1	-0.414*** (0.022)	-0.672*** (0.038)	-1.971*** (0.566)	-1.996*** (0.517)
$(\text{employment})^2$ t-1	-0.001 (0.005)	-0.0002 (0.007)	0.168** (0.083)	0.170** (0.075)
age t-1	0.060*** (0.017)	0.560** (0.239)	0.272** (0.127)	0.302** (0.127)
$(\text{age})^2$ t-1	-0.024*** (0.008)	-0.166** (0.072)	-0.114 (0.166)	-0.124 (0.173)
empl*age t-1	-0.012*** (0.004)	-0.020* (0.012)	0.104 (0.088)	0.111 (0.081)
ltd_liability	0.156*** (0.038)	0.262*** (0.057)	0.390*** (0.063)	0.397*** (0.064)
patent t	0.052 (0.046)	0.056 (0.050)	0.097* (0.059)	0.091 (0.059)
patent t-1	0.039 (0.046)	0.051 (0.051)	0.131** (0.066)	0.125* (0.065)
patent t-2	0.108** (0.052)	0.107** (0.054)	0.153*** (0.058)	0.138** (0.058)
attrition_dead	-0.112*** (0.019)	-0.113*** (0.021)	-0.134*** (0.024)	-
attrition_perm	-0.386*** (0.120)	-0.484*** (0.158)	-0.616*** (0.204)	-
attrition_temp	-0.081 (0.119)	0.017 (0.165)	0.125 (0.204)	-
mills 93	-	-	-	-0.108 (0.213)
mills 94	-	-	-	-0.400** (0.159)
mills 95	-	-	-	-0.371*** (0.118)
mills 96	-	-	-	-0.436*** (0.142)
mills 97	-	-	-	-0.444*** (0.138)
mills 98	-	-	-	-0.305** (0.132)
mills 99	-	-	-	-0.289* (0.167)
constant	0.725*** (0.031)	0.751*** (0.137)	-0.029 (0.087)	-0.037 (0.092)
No. of observations	6820	5549	4098	4098
No. of firms	1271	1175	1029	1029
R^2 within	0.283	0.381	0.226	0.219

*** (**,*) indicates a significance level of 1% (5%, 10%); standard errors in parentheses.

Table 7.6: Fixed-effects and first-difference employment growth regressions II

	FE with AR(1)	FE with AR(1)	FD	FD
Δ employment	-0.045*** (0.015)	-0.045*** (0.015)	-0.0005 (0.025)	-0.0009 (0.025)
employment t-1	-0.674*** (0.038)	-0.673*** (0.038)	-1.970*** (0.565)	-1.953*** (0.561)
$(\text{employment})^2$ t-1	-0.0001 (0.007)	-0.0002 (0.007)	0.168** (0.083)	0.166** (0.082)
age t-1	0.566** (0.239)	0.580** (0.239)	0.274** (0.127)	0.279** (0.126)
$(\text{age})^2$ t-1	-0.168** (0.072)	-0.166** (0.072)	-0.113 (0.165)	-0.118 (0.165)
empl*age t-1	-0.020* (0.012)	-0.019* (0.012)	0.104 (0.088)	0.101 (0.087)
ltd_liability	0.262*** (0.057)	0.263*** (0.057)	0.390*** (0.063)	0.391*** (0.063)
numb_pat t	0.059* (0.032)	-	0.054 (0.034)	-
numb_pat t-1	0.022 (0.029)	-	0.053 (0.034)	-
numb_pat t-2	0.036 (0.023)	-	0.060** (0.027)	-
pat_stock	-	0.089 (0.061)	-	0.164** (0.073)
pat_stock*age	-	-0.030 (0.035)	-	-0.070* (0.042)
attrition_dead	-0.113*** (0.021)	-0.113*** (0.021)	-0.134*** (0.024)	-0.135*** (0.024)
attrition_perm	-0.484*** (0.158)	-0.486*** (0.158)	-0.617*** (0.204)	-0.617*** (0.203)
attrition_temp	0.017 (0.165)	0.016 (0.165)	0.125 (0.204)	0.124 (0.204)
constant	0.747*** (0.136)	0.731*** (0.136)	-0.030 (0.087)	-0.026 (0.087)
No. of observations	5549	5549	4098	4098
No. of firms	1175	1175	1029	1029
R^2 within	0.381	0.381	0.225	0.228

*** (**,*) indicates a significance level of 1% (5%, 10%); standard errors in parentheses.

Unfortunately, using patent grants and citations as a quality indicator is prevented by the nature of the underlying data set: The panel is too short to observe a sufficiently large portion of the time period over which the patents can be granted and cited. According to the fixed-effects model, the effect of number of patent applications is largest in the application year, whereas the first-differencing model still indicates that the greatest effect of patenting activity on employment growth is observed two years later. Patenting stock turns out to be insignificant in the fixed-effects model, perhaps because the underlying assumption of a constantly decreasing impact of patent applications over time is not entirely correct. However, patenting stock has a significant positive effect on growth according to the first-differencing model, yielding further evidence of patenting activity's positive impact on employment growth. As the interaction term between patent stock and firm age indicates, this effect becomes weaker as firms get older. The effect is only slightly significant, but still suggests that patenting activity affects employment growth more strongly the younger the firm. Innovative activity is probably a more important growth factor for very young firms which have yet to develop a company profile and conquer market shares than for more established firms.

7. Conclusion

This paper analyzes the post-entry growth performance of German start-up firms using descriptive methods, fixed-effects and first-differencing dynamic panel data methods. The advantage of these panel data approaches is that they control for time-constant, unobserved heterogeneity. The estimation results obtained can therefore be accepted as unbiased by firm-specific factors like flexibility, entrepreneurial skills, and organizational and technical abilities, which presumably do not vary much over time and exert considerable influence on firm growth. The econometric methods chosen also account for observed constant heterogeneity resulting, for example, from specific industries, regions, or from cohort effects. They further allow correction of attrition bias.

As revealed by the distribution of start-ups across sectors, the transition process of the former East Germany into a more service-oriented, modern economy has taken place rather slowly. The descriptive results further show that, on average, Eastern German start-ups have been larger, have grown faster, had more seed capital at their disposal and have received more financial assistance than Western German firm foundations in the years after reunification. This is to be attributed to the first-mover advantages which can be realized by new firms in a transition economy and to the focus of German subsidization policies on Eastern Germany. Likewise, innovative firms exhibiting patenting activity are larger, endowed with more seed capital and considered to be more eligible for financial assistance than non-patenting firms. However, they do not evince a better average growth performance. The share of patenting start-ups in all start-ups is somewhat lower in Eastern Germany than in Western Germany. Still, Saxony and Thuringia evince larger shares of patenting firms than many Western states.

The multivariate analysis leads to a clear rejection of Gibrat's Law: Employment growth in the surveyed start-ups is negatively related to firm size in the previous year. This result is consistent with the empirical literature on post-entry performance. Firm age has a positive effect on growth at this early stage of the life cycle; this is likely to turn negative as time passes. The latter finding is less common in the literature but has already been revealed by some other studies analyzing very young firms.

The other important finding is that involvement in patenting activities enhances a firm's employment growth performance. This is the overall picture arising from the use of different estimation methods and patent indicators. The positive effect of patenting activity may already be present in the year of patent application, but it most likely peaks two years after application. It seems that with respect to growth, the very act of performing patenting activities is more important than the number of patent applications.

The primary objective of this paper is to contribute to the scarce empirical evidence on the impact of innovative activity on post-entry employment growth. Since patents are mostly used to protect product innovations, the results seem to correspond to the empirical literature which mostly reveals a positive impact of these innovations on employment in established firms. However, the findings cannot be generalized because patents are only a partial indicator of innovativeness. Moreover, since no other innovation indicators are used in the analysis, the result may not only reflect the effect of patents per se, but also innovative activities in general; this could also include the ability to appropriate technical knowledge, which is presumably enhanced by patenting activities. It is clear, however, that the results do not just reflect time-constant, unobserved factors like certain technical abilities or open-mindedness to change, which innovative firms are assumed to have – these are already captured by the fixed effects. Patenting firms do not generally exhibit higher growth rates than their non-patenting counterparts; instead, growth performance depends on their patenting activity over time. There is some evidence that patenting activity is a more important growth factor for very young firms than for more established firms. The results suggest that it is beneficial for young firms to innovate at early stages of their life-cycles in order to become competitive and grow.

References

Almus, M., 2002, *Wachstumsdeterminanten junger Unternehmen. Empirische Analysen für Ost- und Westdeutschland*, ZEW Wirtschaftsanalysen, Baden-Baden: Nomos.

Almus M., Engel D., Nerlinger E., 1999, *Wachstumsdeterminanten junger Unternehmen in den alten und neuen Bundesländern: Ein Vergleich zwischen innovativen und nicht-innovativen Unternehmen*, ZEW Discussion Paper, 99-09.

Almus M., Engel D., Prantl S. 2000, *The „Mannheim Foundation Panels" of the Centre for European Economic Research (ZEW)*, ZEW-Dokumentation, 00-02.

Almus M., Nerlinger E., 1999, Wachstumsdeterminanten junger innovativer Unternehmen: Empirische Ergebnisse für West-Deutschland, *Jahrbücher für Nationalökonomie und Statistik*, 218 (3-4), 257-75.

Almus M., Nerlinger, E., 2000, A Testing "Gibrat's Law" for Young Firms – Empirical Results for West Germany, *Small Business Economics*, 15(1), 1-12.

Almus A, Prantl S., Brüderl J., Stahl K. 2001, *Woywode M. Die ZEW-Gründerstudie – Konzeption und Erhebung*, ZEW-Dokumentation, 01-01.

Audretsch D. B. 1995, Innovation, Growth and Survival, *International Journal of Industrial Organization*, 13(4), 441-57.

Audretsch D.B., Klomp L., Thurik A.R., 1999, "Do Services Differ from Manufacturing? The Post-Entry Performance of Firms in Dutch Services." In *Innovation, Industry Evolution, and Employment*, Audretsch D.B., Thurik A.R., ed. Cambridge University Press, 230-52.

Audretsch D.B., Mahmood T., 1994, Firm Selection and Industry Evolution: The Post-Entry Performance of New Firms, *Journal of Evolutionary Economics*, 4, 243-260.

Becchetti L., Trovato G., 2002, The Determinants of Growth for Small and Medium Sized Firms. The Availability of External Finance, *Small Business Economics*, 19, 291-306.

Blechinger D., Pfeiffer F., 1999, Qualifikation, Beschäftigung und technischer Fortschritt. Empirische Evidenz mit den Daten des Mannheimer Innovationspanels, *Jahrbücher für Nationalökonomie und Statistik*, 218 (1+2), 128-46.

Blechinger D., Kleinknecht A., Licht G., Pfeiffer F., 1998, *The Impact of Innovation on Employment in Europe – An Analysis using CIS Data*, ZEW-Dokumentation, 98-02.

Bloom N., Van Reenen J., 2002, Patents, Real Options and Firm Performance, *Economic Journal*, 112(478), C97-C116.

Brouwer E., Kleinknecht A., Reijnen J.O.N., 1993, Employment Growth and Innovation at the Firm Level, *Journal of Evolutionary Economics*, 3, 153-59.

Cohen W.M., Klepper S., 1996, A Reprise of Size and R&D, *Economic Journal*, 106, 925-51.

Cohen W.M., Goto A., Nagata A., Nelson R.R., Walsh, J.P., 2002, R&D Spillovers, Patents and the Incentives to Innovate in Japan and the United States, *Research Policy*, 31(8-9), 1349-67.

Czarnitzki D., Kraft C., 2004, *On the Profitability of Innovative Assets.* ZEW Discussion Paper, 04-38.

Das, S., 1995, Size, Age and Firm Growth in an Infant Industry: the Computer Hardware Industry in India, *International Journal of Industrial Organization*, 13, 111-26.

Doms M., Dunne T., Roberts M.J., 1995, The Role of Technology Use in the Survival and Growth of Manufacturing Plants, *International Journal of Industrial Organization*, 13(4), 523-42.

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

Evangelista R., Savona M., 2003, Innovation, Employment and Skills in Services: Firm and Sectoral Evidence. *Structural Change and Economic Dynamics*, Special Issue 14(4), 449-74.

Evans D.S., 1987a, The Relationship between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries, *Journal of Industrial Economics*, 35, 567-81.

Evans D.S., 1987b, Tests of Alternatives Theories of Firms Growth, *Journal of Political Economy*, 95(4), 657-74.

Fritsch, Michael, 1990, *Arbeitsplatzentwicklung in Industriebetrieben*. Berlin: de Gruyter.

Geroski P. A., 1995, What Do We Know About Entry?, *International Journal of Industrial Organization*, 13, 421-40.

Geroski P., 1999, *The Growth of Firms in Theory and in Practice*, CEPR Discussion Paper, 2092.

Geroski P., Machin S., Van Reenen J., 1993, The Profitability of Innovating Firms, *Rand Journal of Economics*, 24; 198-211.

Gibrat, Robert, 1931, *Les inégalités économiques; applications: aux inégalités des richesses, à la concentration des entreprises, aux populations des villes, aux statistiques des familles, etc., d'une loi nouvelle, la loi de l'effet proportionnel.* Paris: Librairie du Recueil Sirey.

Goddard J., Wilson J., Blandon P., 2002, Panel Tests for Gibrat's Law for Japanese Manufacturing, *International Journal of Industrial Organization*, 20, 415-33.

Greenhalgh C., Longland M., Bosworth D., 2001, Technological Activity and Employment in a Panel of UK Firms, *Scottish Journal of Political Economy*, 48(3), 260-82.

Greif, S., Schmiedl, D., 2002, *Patentatlas Detuschland – Ausgabe 2002 –. Dynamik und Strukturen der Erfindungstätigkeit.* München: Deutsches Patent- und Markenamt.

Griliches Z., 1990, Patent Statistics as Economic Indicators: a Survey, *Journal of Economic Literature*, 18(4), 1661-707.

Griliches, Z., Mairesse, J., 1984, "Productivity and R&D at the Firm Level." In *R&D, Patents and Productivity*, Griliches, Z., ed. Chicago.

Harhoff D., Stahl K., Woywode M., 1998, Legal Form, Growth and Exit of West German Firms – Empirical Results for Manufacturing, Construction, Trade and Service Industries. *Journal of Industrial Economics*, 46(4), 453-88.

Heckman J.J., 1979, Sample Selection Bias as a Specification Error, *Econometrica*, 47, 153-61.

Honjo Y., 2004, Growth of New Start-up Firms: Evidence from the Japanese Manufacturing Industry, *Applied Economics Letters*, 11, 21-32.

Hsueh L., Tu Y., 2004, Innovation and the Operational Performance of Newly Established Small and Medium Enterprises in Taiwan, *Small Business Economics*, 23(2), 99-113

Jaumandreu J., 2003, Does Innovation Spur Employment? A Firm-Level Analysis Using Spanish CIS Data. mimeo.

Jovanovic, B., 1982, Selection and the Evolution of Industry. *Econometrica*, 50(3), 649-70.

Katsoulacos, Y. S., 1986, *The Employment Effect of Technical Change.* Brighton: Wheatsheaf.

Kirchhoff, B.A. and Phillips, B.D., 1989, "Innovation and Growth Among New Firms in the US Economy." In *Frontiers of Entrepreneurship Research*, Wellesley, MA: Babson College, 173-188.

Kline, S.J., Rosenberg, N., 1986, "An Overview of Innovation." In *The Positive Sum Strategy: Harnessing Technology for Economic Growth*, Landau, R., Rosenberg, N., ed. Washington DC: National Academy Press.

Klomp L., Van Leeuwen G., 2001, Linking Innovation and Firm Performance: A New Approach, *International Journal of the Economics of Business*, 8(3), 343-64.

König H., Licht G., 1995, Patents, R&D and Innovation: Evidence from the Mannheim Innovation Panel, *Ifo Studien*, 41(4), 21-43.

Leo H., Steiner V., 1995, Technological Innovation and Employment at the Firm Level. Vienna: WIFO, Austrian Institute of Economic Research.

Licht G., Zoz K., 1996, *Patents and R&D. An Econometric Investigation Using Applications for German, European and US Patents by German Companies*, ZEW Discussion Paper, 96-19.

Lotti F., Santarelli E., Vivarelli M., 2001, The Relationship Between Size and Growth: The Case of Italian Newborn Firms, *Applied Economics Letters*, 8(7), 451-454.

Lotti F., Santarelli E., Vivarelli M., 2003, Does Gibrat's Law Hold Among Young, Small Firms?, *Journal of Evolutionary Economics*, 13, 213-235.

Lööf H., Heshmati A., 2004, Finance, R&D, and Productivity: Correlation or Causality? Preliminary Version presented at the 10th Meeting of the International Schumpeter Society, 9-12 June 2004; Milan.

Mansfield E., 1962, Entry, Gibrat's Law, and the Growth of Firms, *American Economic Review,* 52(5), 1023-51.

Markusen, A., Hall, P., Glasmeier, A., 1986, *High Tech America, The What, How, Where, and Why of the Sunrise Industries.* Boston: Allen & Unwin.

Mata J., 1994, Firm Growth during Infancy, *Small Business Economics*, 6(1), 27-39.

Penrose, E., 1959, *The Theory of the Growth of the Firm.* Oxford: Basil Blackwell.

Peters B., 2004, *Employment Effects of Different Innovation Activities: Microeconometric Evidence.* ZEW Discussion Paper, 04-73.

Prantl, Susanne, 2002, *Bankruptcy, Subsidized Loans, and Exit Decisions of Start-up Firms.* Online-Ressource, Mannheim, Univ., Diss.

Rottmann H., Ruschinski M., 1997, Beschäftigungswirkungen des technischen Fortschritts. Eine Paneldaten-Analyse für Unternehmen des Verarbeitenden Gewerbes in Deutschland, *Ifo Studien*, 43, 55-70.

Smolny, Werner, 1998a, *Endogenous Innovations and Knowledge Spillovers – A Theoretical and Empirical Analysis.* ZEW Economic Studies 12, Heidelberg: Physica-Verlag.

Smolny W., 1998b, Innovation, Prices, and Employment – A Theoretical Model and an Empirical Application for West German Manufacturing Firms, *Journal of Industrial Economics,* 46, 359-81.

Tether B.S., 1997, Growth Diversity Amongst Innovative and Technology-based New and Small Firms: An Interpretation. New Technology, *Work and Employment*, 12(2), 91-107.

Van Reenen J., 1997, Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms. *Journal of Labour Economics*, 15(2), 255-84

Wooldridge, J.M., 2002, *Econometric Analysis of Cross Section and Panel Data.* Cambridge, Massachusetts: MIT Press.