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Patenting Behaviour and Employment Growth in German Start-up Firms

A Panel Data Analysis

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Non-Technical Summary

Despite the perpetual debate surrounding the consequences of technological change for employment, there is only relatively little microeconometric work on the effect of innovations on corporate employment growth. The sign of this effect is theoretically ambiguous: While increasing the level of demand, product innovations might replace existing products and reduce price elasticity of demand so that output and employment might decrease as well; process innovations reduce production costs but often imply labour-saving progress. This paper analyses empirically the relationship between innovative activity and employment growth at the micro-level using panel data on German start-up firms followed through the 1990s. Patent data from the German Patent Office are used to provide an indication of innovative activity. Attention is also paid to the size-age-growth relationship.

The results reveal that small firms grow much faster than larger ones, while firm age affects employment growth rather positively at this early stage of the life cycle in which the firms are observed. Using different patent indicators, it further turns out that patenting activity has a positive effect on employment growth. However, 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 the effect is greatest two years after patent application and that it is larger for younger firms than for older ones. Moreover, it is apparently rather the very act of applying for patents than the number of patent applications that matters for the growth performance of a firm.

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Abstract: The effect of innovations on employment at the firm level is theoretically ambiguous. The present paper analyses this relationship using panel data on German start-up firms as well as German patent data. It employs different indicators of patenting activity. By applying fixed-effects and first-differencing panel data methods it is shown that patenting activity has a positive effect on employment growth that is typically most pronounced in the second year after application. The effect seems to diminish with firm age. Patenting firms do not generally exhibit higher growth rates than their non-patenting counterparts; instead, growth performance depends on their patenting activity over time.

Keywords: employment growth, patents, Gibrat´s law, dynamic panel data models

JEL-Classification: D92, L25, C23

1. Introduction

Innovation is universally regarded as a major source of economic growth. Likewise, 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 length of time over which a competitive advantage lasts 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 analysing the impact of R&D and innovations on productivity, sales, and market value at the firm level. However, despite the ongoing debate on the consequences technological change has for employment, there is only relatively little microeconometric work dealing with the effect of innovations on corporate employment growth. The sign of this effect, derived from theoretical models, is not clear: While increasing the 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 labour-saving progress. This paper analyses empirically 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 focuses on other potential determinants of post-entry performance, particularly firm size. Fixed-effects as well as first-differencing panel estimators are applied to the data.

The paper is structured as follows. The next section outlines the theoretical approaches to employment growth at the firm level while focusing on the effects of firm size and innovative activity. The methodological problems encountered when analysing the relationship between innovative activity and corporate growth are illustrated in the third section. Section 4 surveys the relevant empirical literature. The econometric models used for the empirical analysis are explained in section 5. A description of the underlying data set and the characteristics of patenting and non-patenting firms are given in section 6. Section 7 presents the results, and section 8 concludes.

2. Theoretical Background

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 effort. 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 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 regarding the size-growth and age-growth relationship should be given.

The effect of firm size

The related theoretical literature has paid special attention to the effect of firm size on corporate growth and to the 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 the firm size distribution tends to become increasingly concentrated over time (Goddard et al. 2002).

Various theoretical approaches are contradictory to 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 organisational 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 firms' industry. 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 emphasises 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 organisational 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.

The effect of firm age

As far as the age of a firm is concerned, learn-theoretic models like the one 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).

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 labour markets and the characteristics of the innovation itself exist (Blechinger et al. 1998). Innovations can be categorised 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 labour (capital) augmenting type if they allow reduction of labour (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, labour 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 labour and capital (i.e., the degree to which the firm can substitute capital by the relatively more cost-efficient factor labour in the case of the labour 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 to 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 of this indirect effect, the employment of the firm in question might decline (Smolny 1998b).

The net effect on employment depends on the relative strength of the positive quantity effect and the negative price effect. However, the positive quantity effect is more likely to prevail. In the extreme case in which specialised 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. As a consequence of these results, a negative relation between employment growth and industry age arises. In the early stage of the industry life-cycle, product innovations (i.e, the introduction of a new product and further substantial product enhancements) prevail. In later stages in which the product is already largely standardised, 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.

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. It has to be controlled for all of these factors 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 it is controlled 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, the 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 the failure 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, the correction for selectivity is time-invariant and 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 next 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 therefore 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. Empirical evidence suggests that employment *size* has a significant impact on number of patents and innovations (e.g., Schwalbach and Zimmermann 1991, Entorf and Pohlmeier 1990, König and Licht 1995, Acs and Audretsch 1990).[1] However, there is no study known to the author which documents employment *growth's* effect on innovative activity. 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 the number of employees might be misleading. Innovations may affect various skill levels of employment very differently. There is usually a complementarity between new technology and skilled labour; this causes the demand for skilled labour to rise with technical progress while the demand for unskilled labour declines (Blechinger et al. 1998). It is therefore desirable to have employment data distinguishing the skills required to do the job. Unfortunately, no such information 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 applica-

[1] Schwalbach and Zimmermann show for Western Germany that number of patents increases with firm size. However, they find that the propensity to patent, i.e., number of patents per number of inventions, is lower for the largest firms than for SMEs. Acs and Audretsch show that the most innovative US firms are large corporations. Still, they observe that innovation rates, i.e., number of innovations per thousand employees, are larger in small firms.

tions or grants. On the one hand, patents are inventions and insofar the output of research activity. The application for a patent 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 the profits from its 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 analysed, 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 wait 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.

Moreover, 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 industry and type of innovation. 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 until a firm has fully adapted its production to the new technique/product in question or until the market for the new product is saturated. 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. Empirical Literature

Turnover and labour 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 view of the empirical analysis in section 7, this survey of related empirical literature first provides a short summary of the extensive empirical work dealing with the relations between employment growth and firm size and age; it then focuses on the impact of innovative activity.

Survey articles summarising the empirical evidence for the US (e.g., Sutton 1997) have detected some "statistical regularities": Firm size and age are positively related to likelihood of survival, while growth rates decrease with size and age. Similar results have been found in the European context, but the links between growth and size and age are somewhat more ambiguous here (Audretsch 2002). At least for firms exceeding a certain size (Becchetti and Trovato 2002) and for those in specific sectors of the economy (Audretsch et al. 2002, Almus 2002), growth and size seem to be independent of one another. Audretsch et al. (2002) ascribe the insignificant size coefficient in their analysis of the Dutch hospitality sector to the low MES in the service sector which allows small firms to be competitive and stay in the market without growing. According to Geroski (1999), past and recent econometric work has suggested that growth rates are random and driven by exogenous events. He states that the estimated size coefficient is mostly small and that the evidence supporting convergence in firm size is not all that strong. Firms in the same industry rather converge toward different steady-state sizes. They make large and infrequent changes in output and employment, which is consistent with the observation that the production of innovations is erratic as well – firms neither grow nor innovate consistently. However, Mata (1994) and Goddard et al. (2002) illustrate the impact which 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 a more pronounced negative influence of firm size on growth compared to when standard cross-sectional methods are applied. This finding is corroborated by Das (1995) and Liu et al. (1999), who compare the results of OLS and fixed-effects estimations of employment growth.

At least up to a certain age, most empirical work reveals a negative relationship between employment growth and age (e.g., Evans 1987a/b, Liu et al. 1999, Heshmati 2001, Bechetti and Trovato 2002); in other words, they confirm Jovanovic´s model. However, studies which analyse firms in infant industries or very young firms often show a positive impact of age on growth that diminishes with age (Das 1995, Almus et al. 1999). This suggests that the returns on learning are increasing 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.

Empirical work on the effect of innovations on employment growth yields very mixed results. Katsoulacos' (1986) hypothesis that product innovations stimulate employment and process innovations are labour-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). Analysing 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 favour of a positive effect of process innovations on employment growth was found by Doms et al. (1994) for US manufacturing plants and by Klomp and Van Leeuwen (2001) for Dutch firms mostly involved in the manufacturing sector. 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 rationalisation reasons (and not in order to improve product quality or to fulfil 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, Goddard et al., Heshmati, Liu et al., Mata, and Rottmann and Ruschinski applied panel data techniques (fixed- or random-effects models) based on annual growth rates; Smolny performed pooled OLS regressions. All other studies used 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 the Arellano and Bond's first-differencing model for UK manufacturing firm data and finds a positive relationship between number of successful innovations[2] 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

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

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 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.

To conclude this survey, some stylised facts derived by Tether (1997) regarding employment creation in innovative and technology-based new and small firms are reproduced: 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. These stylised facts may be one explanation as to why the empirical evidence regarding the effects of innovative activity on corporate employment growth is so diverse.

5. Econometric Model

The employment growth of firm i ($i = 1...N$) in period t ($t = 1...T$) can be presented by the model

$$g_{it} = x_{it}\beta + c_i + u_{it}. \qquad 1$$

g_{it} is the logarithmic employment growth rate, i.e., $g_{it} = y_{it} - y_{i,t-1}$ with y_{it} being the logarithm of employment of firm *i* at period *t*. β is a vector of unknown parameters, x_{it} a set of explanatory variables, c_i an unobserved, time-constant, firm-specific effect, and u_{it} the error term. Panel data methods treating c_i either as fixed or random can be used to estimate equation 1. The term c_i captures the unobserved heterogeneity across firms as far as it is due to time-constant characteristics.

Empirical studies using panel data models to analyse employment growth usually choose a fixed-effects or first-differencing method in order to account for unobserved heterogeneity. Applying the Hausman test, fixed-effects methods often turn out to be superior to the random effects approach (e.g., Mata 1994, Das 1995, Rottmann and Ruschinski 1997, Liu et al.1999).

This can be explained by the probable correlation of unobserved, time-invariant, firm-specific factors like entrepreneurial skills or technical knowledge with the explanatory variables, such as innovation indicators. If there is correlation between the unobserved individual effects and the covariates, the random effects model leads to inconsistent estimates.

The fixed-effects method is usually applied to the transformation of equation 1, which eliminates c_i by subtracting the averages over $t = 1...T$ from each term:

$$g_{it} - \overline{g}_i = (x_{it} - \overline{x}_i)\beta + u_{it} - \overline{u}_i . \qquad 2$$

The u_{it} are assumed to be homoscedastic and serially uncorrelated: $E(u_i u_i' \mid (x_i, c_i) = \sigma_u^2 \mathrm{I}_T$.

The first-differencing method eliminates the fixed effects by taking the first differences of equation 1:

$$g_{it} - g_{i,t-1} = (x_{it} - x_{i,t-1})\beta + u_{it} - u_{i,t-1}$$

$$\Leftrightarrow \qquad \Delta g_{it} = \Delta x_{it}\beta + \Delta u_{it} . \qquad 3$$

Here, the Δu_{it} , in the following denoted as e_{it} , are assumed to be homoscedastic and serially uncorrelated: $E(e_i e_i' \mid (x_i, c_i) = \sigma_e^2 \mathrm{I}_{T-1}$. Using $u_{it} = u_{i,t-1} + e_{it}$ makes it clear that no serial correlation in the e_{it} implies that u_{it} is a random walk. Thus, in contrast to the fixed-effects model, the first-differencing model assumes substantial serial dependence in u_{it} (Wooldridge 2002). Both equation 2 and equation 3 can be consistently estimated by pooled OLS, assuming that $E(u_{it} \mid x_i, c_i) = 0$, $t = 1...T$. The relative efficiency of the fixed-effects and first-differencing methods depends on the appropriateness of their assumption concerning the serial dependence of u_{it} .

Turning now to the testing of Gibrat´s law, the following model has commonly been used as a starting point:

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

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).

For a test of Gibrat´s law using panel data, Goddard et al. (2002) suggest the following reparameterisation of the model:

$$y_{it} - y_{i,t-1} = \alpha_i(1-\rho) + \beta y_{i,t-1} + \rho(y_{i,t-1} - y_{i,t-2}) + \eta_{it}; \quad \eta_{it} = e_{it} + \rho\beta y_{i,t-2}. \qquad 4$$

Estimation of equation 4 using the fixed-effects approach leads to biased coefficients. If strictly exogenous instruments are available for the lagged dependent variable on the right-hand side, equation 4 can be estimated by pooled 2SLS using the fixed-effects method. This is not the case for the data set used in this study. To instrument $y_{i,t-1}$ by its own lags does not allow for consistent estimation because these lags are, just like $y_{i,t-1}$ itself, connected to the error term via the arithmetic mean $\bar{y}_i$. The resulting bias only diminishes as $T \to \infty$. This is of little help when the panel data set in question is relatively small as in the present context (see the data description in the next section). Nevertheless, as Goddard et al. (2002) hold, these problems “do not present insurmountable obstacles” to using the fixed-effects estimator to test Gibrat´s law. It is in any case preferable to cross-sectional tests due to its important advantage of accounting for heterogeneity. It will be used as a standard of reference in this study.

If strictly exogenous instruments are not available but the assumption of sequential exogeneity – under which the error term is allowed to be correlated with future values of the explanatory variables – holds, the first-differencing method is more appropriate than the fixed-effects approach (Wooldridge 2002). The first-differenced version of equation 4 can then be estimated by pooled 2SLS using lags of $y_{i,t-1}$ as instruments. In section 7, equation 4 will be estimated in two ways: The first involves performing a one-step estimation of the fixed-effects model, and the second includes a 2SLS estimation of the first-differencing model using lagged values of $y_{i,t-1}$ as instruments.

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. Before applying a method correcting for selection bias, a simple test revealing whether such bias really exists is performed. A lead of a selection indicator, $s_{i,t+1}$, taking the value 1 if unit *i* is still in the panel in the following period and zero otherwise, is included in a pooled regression of the growth model. If the coefficient of the selection indicator is significant, selection bias is present in the data. According to this test, temporary drop-outs do not cause any bias within the chosen econometric approach in this study (see section 7). Therefore, only a method correcting for attrition bias is applied and described in the following.

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 (2002:585ff) is used. Let s_{it} denote a selection indicator where $s_{it} = 1$ if (g_{it}, x_{it}) are observed in *t* and $s_{it} = 0$ if they are 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; $s_{it} = 1$ thus implies $s_{i1},..., s_{i,t-1} = 1$.

Wooldridge (2002) recommends applying the selection correction to the first-differencing model (equation 3). As a first step, the selection equation

$$s_{it} = 1(w_{it}\delta_t + v_{it} > 0), \qquad v_{it}\left|\{w_{it}, s_{i,t-1} = 1\}\right. \sim \text{Normal}(0,1) \qquad 5$$

is estimated by a probit model for each $t \geq 2$. w_{it} should contain all elements of x_{it} to avoid exclusion restrictions on a reduced-form equation. However, for $s_{it} = 0$, contemporary terms in *x* will generally not be observed. Therefore, *w* can only include lagged values of *x*, variables that can be computed (like age), or aggregate variables. Equation 5 should include at least one significant explanatory variable which is not part of the structural equation. Otherwise, the parameters in the structural equation are, in fact, identified, but severe collinearity may be present among the regressors.

The inverse Mills ratios $\hat{\lambda}_{it}$ are calculated for each of the $T-1$ probit estimations of equation 5. These are then included in equation 3, yielding

$$\Delta g_{it} = \Delta x_{it}\beta + \rho_2 d2_t \hat{\lambda}_{it} + ... + \rho_T dT_t \hat{\lambda}_{it} + error_{it}, \qquad 6$$

where $d2_t$ through dT_t are time dummies. Equation 6 is then estimated by 2SLS instrumenting the $y_{i,t-1}$ contained in $x_{i,t}$ with its own lagged values. Attrition bias can be tested by a joint test of $H_0 : \rho_t = 0$ for $t = 2,...,T$.

6. Description of Data

The empirical analysis is based on a sample of German firms founded between 1990 and 1993. For its configuration 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 active, legally independent firms. The data contain information on variables like industry (five-digit code), legal status, foundation date, region (district), 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 oversampled 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 about their failure. The sample is confined to firms founded between 1990 and 1997 (more than 90% were founded between 1990 and 1993) in the manufacturing, construction, trade, transport & 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.[3] For this study's analysis, legally dependent firms, firms which were not truly new foundations but take-overs, 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 (communication & transporting, retail trade, and consumption-related services)[4] were not 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 were also 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.

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

[4] 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.

This firm data set has been merged with German patent data. 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 combination of the two data sets allows 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 of the 1,357 firms remaining in the sample (3.2 %) applied for one or more patents between 1990 and 1999 (see table 1). Altogether, the sampled firms made 128 patent applications in that period, 21 (16.4%) of which were applied for at the EPO and 56 (43.8%) of which were granted up to the year 2003.[5] 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 & intermediate trade sector and – to a very small extent – from construction.

As a comparison with the sectoral distribution of patenting firms shows, sectors obviously differ by mean number 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. Still, the share of patent applications from both manufacturing and business-related services exceeds by far the weight of these sectors – as measured by the number of firms found in each – in the economy. The opposite holds for wholesale & intermediate trade and, in particular, construction.

Overall, the distribution of patent applications across patenting firms is highly skewed. Figure 1 shows how many firms applied for a specific number of patents. 43% 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% of the patenting firms applied for more than ten patents and account for more than a quarter of the total number of patent applications.

[5] 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.

Table 1: Descriptive Statistics

	All Firms	Non-Patenting Firms	Patenting Firms
Number of firms	1,387	1313 (96.8%)	44 (3.2%)
No. of patent applications	128	-	128
No. of EPO patent applications	21	-	21
No. of granted patents	56	-	56
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***
Mean firm age	3.3	3.3	3.5
Mean firm age at patent application	-	-	3.0
Firms by earliest legal form (%)[6]			
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*
Highest lvl., founder education (%)			
doctoral level	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
Year of foundation (%)			
1990	26.7	26.6	31.8
1991	24.4	24.6	18.2
1992	21.8	21.8	20.5
1993	19.2	19.3	15.9
after 1993	7.9	7.7	13.6

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

Comparing the patenting and non-patenting firms, it is apparent that average annual growth rates do not significantly differ between them. Further analysis shows that the distribution of growth rates of patenting firms exhibits less variance and is less skewed, i.e., the rates are more evenly distributed across the observed (smaller) range of growth rates. The share of firms exhibiting growth rates near the outer edge of the distribution is higher than among non-patenting firms. Following Freel (2000), Figure 2 categorises the employment trend into four

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

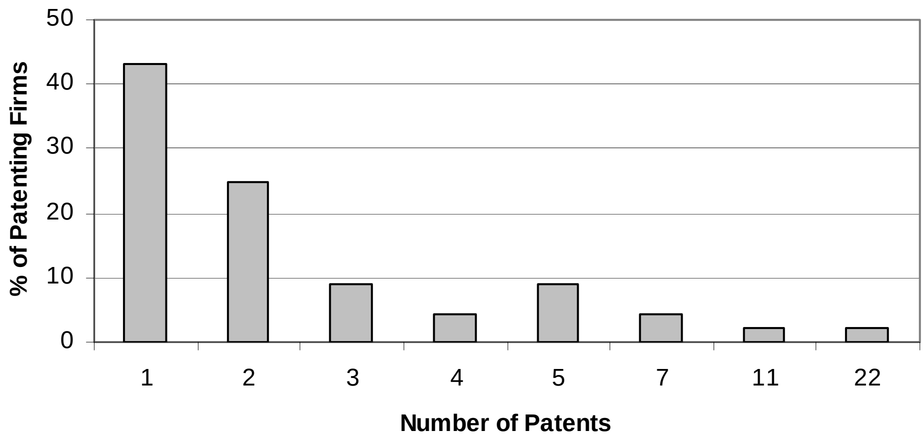

Figure 1: Share of Patenting Firms Applying for a Specific Number of Patents, 1990-1999

groups: declining (negative growth rate), stable (growth rate equal to zero), growth (positive growth rate lower than that of the sample's upper quartile), and super growth (growth rate at least as large as that of the sample's upper quartile). It is demonstrated that patenting firms exhibit declining employment more often than their non-patenting counterparts, but also evince much less zero growth. While both kinds of firms hardly differ in their share of firms exhibiting growth, patenting firms show super growth somewhat more often than non-patenting firms.

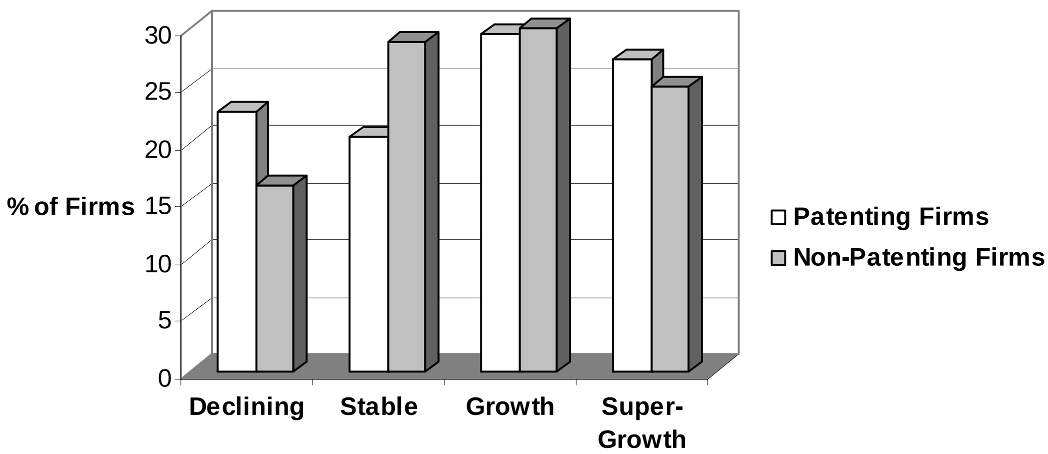

Figure 2: Share of Firms Falling into Specific Growth Categories

As a consequence of these results, it appears that some of the stylised facts found by Tether (1997) regarding innovative, technology-based firms have to be reconsidered: Firstly, innovative firms do not generally outperform non-innovating firms in terms of employment growth.

Secondly, it is true that the growth rate distribution of the patenting firms in the sample is skewed and exhibits a high variance, as has been generally noted of young, small firms; it is, however, less skewed and variant than the growth rate distribution of non-patenting firms. Thirdly, the share of firms showing exceptionally high growth rates is not that small among patenting firms; it is somewhat larger than the corresponding share of non-patenting firms and amounts to over 27%.

Table 1 further indicates that patenting firms have a higher probability of survival than their non-patenting counterparts. However, the difference is only weakly 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 mean age (the average age of a firm over the period) of patenting firms at the time of patent application is slightly lower than their mean age over the observation period, suggesting that firms exhibit patenting activity rather 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 ones. Comparing firm founders' highest level of education shows that founders of patenting firms possess doctoral degrees more often than those of non-patenting companies. Somewhat surprisingly, they do not have other academic degrees more often. There is no significant difference between the two firm types concerning the distribution over the year of foundation.

7. Empirical Results

The econometric analysis incorporates the estimation of an employment growth equation using fixed-effects as well as first-differencing methods. The appropriateness of a random effects model can be rejected by the Hausman test. The analysis is based on equation 4, i.e., growth is explained by firm size and growth (lagged one period). Following Evans (1987a/b), firm age, squared terms of both size and age, and an interaction term between size and age are also included in the regressions. Further micro-level variables consisting of legal status and a measure of each firm's patenting activity are also accounted for. Patenting activity is measured by number of patent applications, a variable indicating whether each firm applied for any patents during the year of observation, or patent stock. The latter is a weighted index of the number of current-period and past patent applications. 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 modelling and empirical evidence concerning employment growth and innovative activity as cited in section 3: Current employment growth has no significant influence on current or future patenting activity.

Finally, either indicator variables of possible selection bias or selection correction terms are included in the regressions. The three indicators of selection bias refer to temporary dropouts, attrition due to death, and attrition due to other reasons. In the first-differencing model with selection correction, the Mills ratios obtained from estimating equation 5 are inserted as correction terms. The names and definitions of the explanatory variables are given in table 2.

Table 2: 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 or stock company
numb_pat	number of patent applications in current period
patent	indicator of whether firm applied for at least one patent in current period
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 the subsequent period, 0 otherwise
attr_perm	leading selection indicator taking value 1 if firm leaves the panel permanently for reasons other than death in the subsequent period, 0 otherwise
att_temp	leading selection indicator taking value 1 if firm leaves the panel temporarily in the subsequent period, 0 otherwise
mills 93-99	inverse Mills ratios estimated from probit regressions (equation 5)

Table 3 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 where the error term u_{it} is assumed to follow a first-order autoregressive process, i.e., $u_{it} = \rho u_{i,t-1} + e_{it}$. From section 5 it is clear that the introduction of serial dependence into the disturbances makes the fixed-effects model more similar to the first-differencing model. 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 including the estimated coefficients of the Mills ratios.

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.

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 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. However, this correlation might not be due to firms smoothing out their growth rates over time as suggested by Penrose. It is rather due to unobserved effects like a specific economic situation lasting several periods or a firm's temporary competitive advantage. When controlling for such effects, 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 3 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 3: All four estimations show a highly significant negative effect of previous firm size on current growth, albeit the positive sign of the quadratic term – which is significant in the first-differencing models – indicates that this negative effect diminishes with size. But the turning point at which the negative effect turns positive 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; it may be ex plained 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 will 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 1998, 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. Public firms and 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 a patent 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 even already indicates a somewhat significant positive effect 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 models 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 in due time in order to be able to fully exploit the competitive advantage implied by the patent.

An obvious weakness of the present model specification is the absence of any financial indicators serving as explanatory variables. Patenting activity might just be a signal of available internal financing, an important factor for growth. Unfortunately, there are no time-varying

Table 3: Fixed-effects and First-difference Employment Growth Regressions I

	FE	***FE with AR(1)***	***FD***	***FD with selection correction***
	coefficient	*coefficient*	*coefficient*	*coefficient*
	(std. error)	*(std. error)*	*(std. error)*	*(std. error)*
Δ employment t-1	0.041***	-0.045***	-0.001	-0.031
	(-0.011)	(0.015)	(0.025)	(0.020)
employment t-1	-0.414***	-0.672***	-1.971***	-1.996***
	(0.022)	(0.038)	(0.566)	(0.517)
$(\text{employment})^2$ t-1	-0.001	-0.0002	0.168**	0.170**
	(0.005)	(0.007)	(0.083)	(0.075)
age t-1	0.060***	0.560**	0.272**	0.302**
	(0.017)	(0.239)	(0.127)	(0.127)
$(\text{age})^2$ t-1	-0.024***	-0.166**	-0.114	-0.124
	(0.008)	(0.072)	(0.166)	(0.173)
empl*age t-1	-0.012***	-0.020*	0.104	0.111
	(0.004)	(0.012)	(0.088)	(0.081)
ltd_liability	0.156***	0.262***	0.390***	0.397***
	(0.038)	(0.057)	(0.063)	(0.064)
patent t	0.052	0.056	0.097*	0.091
	(0.046)	(0.050)	(0.059)	(0.059)
patent t-1	0.039	0.051	0.131**	0.125*
	(0.046)	(0.051)	(0.066)	(0.065)
patent t-2	0.108**	0.107**	0.153***	0.138**
	(0.052)	(0.054)	(0.058)	(0.058)
attrition_dead	-0.112***	-0.113***	-0.134***	-
	(0.019)	(0.021)	(0.024)	
attrition_perm	-0.386***	-0.484***	-0.616***	-
	(0.120)	(0.158)	(0.204)	
attrition_temp	-0.081	0.017	0.125	-
	(0.119)	(0.165)	(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***	0.751***	-0.029	-0.037
	(0.031)	(0.137)	(0.087)	(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%).

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 a firm's financial situation. However, the corresponding variable proves to be insignificant in the estimations.

Columns 2 - 4 in table 3 refer to estimations without selection correction. The fixed-effects and first-differencing procedures only correct for selection bias due to time-invariant individual effects. The models only contain leading selection indicators which allow testing of selectivity as a result of individual time-specific components. These are the indicators of permanent drop-out due to firm closure, permanent drop-out due to other reasons, and temporary drop out in the subsequent period. 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 (2003), attrition due to firm closure is preceded by bad 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.

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 at the first stage and as explanatory variables at the second stage. The probit estimations include practically all of the variables used in the 2SLS regression except for current legal status. The latter is not available for $s_{it} = 0$ and is replaced by its one-year-lagged value, which seems to be a good approximation given the low variation of this variable over time. 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 has received start-up assistance, and indicators of the payment history of each firm. They all lend significant explanatory potential to the selection regressions.

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 (with the exception of the coefficient of lagged employment growth). This negative coefficient is much larger in absolute value in the model with selection correction than in the simple first-differencing model; it misses the 10% level of significance by two percentage points. Hence, the selection correction model yields a result which is more consistent with that of the AR(1)-fixed-effects model. However, the similarity between both first-differencing models with respect to all of the other coefficients indicates that the leading selection indicators already correct for the bulk of the attrition bias.

Table 4 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 measurements, namely number of patent applications and patent stock. The latter 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% (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 patent indicator's different lags used in table 3 may be estimated somewhat imprecisely because of the correlation of a firm's patenting behaviour 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.

Comparing the results of the second and fourth columns with the corresponding estimations in table 3, 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. It seems that the relationship between growth and number of applications is not linear. 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 positive significant effect on growth accord ing 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 weakly 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

Table 4: Fixed-effects and First-difference Employment Growth Regressions II

	FE with AR(1) coefficient (std. error)	*FE with AR(1)* coefficient (std. error)	*FD* coefficient (std. error)	*FD* coefficient (std. error)
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%).

which still have to develop a company profile and conquer market shares than for more established firms.

8. Conclusion

This paper analyses the post-entry growth performance of German start-up firms using 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 unadulterated by firm-specific factors like flexibility, entrepreneurial skills, and organisational 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 or regions or from cohort effects. Moreover, the first-differencing model allows the correction of biases due to panel attrition. However, it turns out that these biases can be eliminated to a large extent by simply introducing selection indicators into the regression.

The 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 was to be expected because the sample consists exclusively of start-up firms, which usually start with a suboptimal size and are forced to grow in order to survive. Firm age has a positive effect on growth at that early stage of the life cycle; this is likely to turn negative as time passes.

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. There is some evidence that patenting activity is a more important growth factor for very young firms than for more established firms. Moreover, it seems that with respect to growth, the very act of performing patenting activities is more important than number of patent applications. This finding might be due to the varying quality and economic significance of patents. Using patent grants and citations as a quality indicator, however, 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.

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 firm-specific 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.

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