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Patents and R&D
An Econometric Investigation Using Applications for German, European and US Patents by German Companies

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Non-technical summary

Patents and the expenditures on research and development (R&D) are the most widely used indicators in the economic analysis of technical change. Both indicators are used to assess the technological strength of countries or sectors as a whole or with respect to certain areas of technology. The continual development of these indicators commonly interpreted towards changes of the innovative capabilities. At the firm level patent numbers and R&D are used as indicators of the technological capabilities of firms to assess the productivity effects of innovations or the technological strategies of firms. Although many studies use this indicators more or less as substitutes, the relationship between R&D expenditure and patents was the subject only of a few studies. It is well-known that both indicators have strengths and weaknesses. R&D expenditure suffers from the under-counting of R&D in small firms. Not all inventions were protected by patents, either because patents are a weak instrument to protect intellectual property or because patents not only protect but also diffuse knowledge to competitors. R&D expenditures represent the most important input into the innovation process whereas a patent is an (intermediate) result of an innovation process. Therefore, it is questionable whether there is a close correlation between patent numbers and R&D expenditures.

Based on the data of the Mannheim Innovation panel this paper explores the relationship between R&D expenditures and patents at the firm level. It is shown that the share of R&D performing firms is strictly increasing with firm size. The share of firms applying for patents exhibits an even steeper increase with firm size. Moreover, large firms more likely apply for patents in more than one country. In comparison to the patent applications at the European Patent Office or other international patent offices, the German patent system seems to be especially important to small and medium sized enterprises.

The number of patent applications depends on firm's own R&D expenditure but does not depend on R&D spent by competitors. Our study implies that the ability of R&D to generate patents is increasing with the amount spent on R&D. Even when we take into account a variety of firm characteristics as well as R&D expenditure the number of patent applications is increasing with firm size. The same is true with respect to the propability that a firm applies for a patent. This result can be explained by a lack of information on the patent system by small firms. Alternatively small firms prefer other mechanisms (e.g. secrecy) to protect their innovation or distrust patents, maybe because of the large costs involved in defending a patent. Another explanation of this result would be that small firms - on average - are more engaged in incremental innovation which does not fulfill the novelty requirement of patents. Moreover, large firms more probably apply for patent due to institutional requirements (e.g. Arbeitnehmererfinderrecht). In addition, firms apply for patents because patents are used in cross-licencing agreements with other firms.

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by

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Abstract

Based on the data of the first wave of the Mannheim Innovation panel, this paper explores the link between R&D expenditures and patents. Our data allow a detailed analysis of the firm size distribution of R&D and patent applications at different patent offices. It is shown that the share of R&D performing firms is strictly increasing with firm size. The share of firms applying for patents shows an even steeper increase with firm size. Moreover, large firms more likely apply for patents in more than one country. The home patent office seems to be especially important for small firms. Using various count data models, the paper explores the relationship between R&D and patents at the firm level. We carefully test several distributional assumptions for count data models. A negbin hurdle model seems to be the most appropriate count data model for our data as the decision to patent inventions and the productivity of R&D are ruled by different mechanisms. Our estimates point towards significant returns to scale of R&D. Furthermore, the empirical results can be interpreted towards minor and insignificant spillover effects. Even after controlling for a variety of firm characteristics, firm size exhibits a large effect on the propensity to patent.

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1 Introduction

Patents and R&D are commonly used indicators in the economic analysis of technical change (see e. g. Griliches 1990, Pavitt 1985). At the aggregate level both measures are used to assess the technological strength of countries and industries. The continual development of these indicators is commonly interpreted towards changes of the innovative capabilities (e.g. NIW et al. 1996, National Science Board 1996). In firm level analyses, patent numbers and R&D are used as indicators of the technological capacity of firms to study productivity effects of innovation (e.g. Lach 1995) or to test the famous Schumpeterian hypothesis (see Cohen and Levin 1989).

The usage of patent information and R&D figures as economic indicators has been steadily improved and refined in recent years. The quality of both indicators as well as the availability of this kind of data has increased and measurement standards were developed (see e.g. OECD 1993, 1994). Now, computerisation of patent offices enables detailed analyses of patent information. R&D surveys are performed on a regular basis in all developed economies. Therefore, it seems worthwhile to look more closely at the relationship between both indicators at the firm level.

It has often been recognised that R&D and patents capture different aspects of the innovation process. R&D expenditures or the number of R&D employees can be viewed as a measure of the resources devoted to the innovation process. But R&D represents only a part of the resources necessary to launch new products and processes. In addition, traditional R&D surveys often fail to uncover R&D in small firms (see e.g. Kleinknecht and van Reijnen 1991). On the other hand patents reflect the results of innovation processes. But as for R&D, only a part of the innovation output is captured by patents. Patents reflect just one aspect: the means by which firms protect an innovation. However, patenting is only one method to protect profits originating from new products or processes from imitation by potential competitors (see Levin et al. 1987 for the US, König and Licht 1995 for Germany). Moreover, computerisation of patent offices decreased the costs of inferring technological information from patent documents held by competitors in recent years. As a consequence the value of patent protection decreases. As shown by Horstmann, MacDonald, and Slivinski (1985) it is rationale not to patent all inventions if patent applications contain information on technological opportunities.

The relationship between patents and R&D has been studied by various authors in recent years. Pavitt (1985) concludes that small firms tend to patent more per unit R&D than large firms. Scherer (1983) finds remarkable differences in patenting behaviour within technology groups not being explained by R&D efforts. Using a data set of large German companies, Zimmermann und Schwalbach (1991) find only weak correlations between various firm characteristics like risk, diversification, export share and patenting behaviour. In the absence of R&D data, firm size turns out to be an important determinant of the number of patents held by a company. Evenson (1993) stresses the importance of foreign demand for the propensity to patent. Crépon and Duguet (1996, 1997) study the relation of R&D and patent application at the firm level using a sample of French firms. Using a wide variety of count data models, they find a R&D elasticity of patent numbers of just around 1 and a strong negative effect of R&D rivalry on patent activity.

Our study builds on this literature to explore the relationship between patents and R&D. It extends the previous literature in at least four aspects. First, previous literature is mainly based on data of US or French enterprises. Our study supplements the literature with the case of the West-Germany economy which is the world's third largest patentee. Second, we study patent applications at various patent offices for a large sample of manufacturing firms, which enable us to compare patenting behaviour in the home and the export market. Existing empirical evidence only looks at one patent office. Our data set provides us with information on patent applications at various patent offices which allows us to draw some inferences with regard to national and international patenting activities. Third, our data enables us to control for the effect of certain firm characteristics unavailable in most studies. Finally, we distinguish between the decision with respect to the first patent and the decision for additional patents. We carefully test the statistical properties of various count data models and adopt a negative binomial hurdle model to take account for unobserved heterogeneity with respect to the propensity to patent as well as the ability of firms to generate inventions.

The paper is organised as follows: Section 2 sets up the problem by describing patenting behaviour and R&D at the firm level. It gives some evidence on differences of patenting and not patenting firms as depicted by indicators of innovation processes. Section 3 shortly outlines a theoretical framework for investigating the relation of R&D and patents at the firm level. In section 4 we describe the necessary steps to implement the theoretical framework to the data set at hand. Section 5 introduces the empirical model. We discuss various count data approaches to the patent-R&D relationship and present some specification tests. In section 6 we present the regression estimates and take a closer look at the elasticity of patent applications to R&D. Finally, section 7 summarizes our results and draws some conclusions for further research.

2 Patents, R&D and Innovation at the Firm Level

Although patents and R&D are regularly used indicators of technical change at the macro and the micro level, only a few studies seek to analyze their relation at a micro level. R&D reflects the input side whereas patents can be viewed as a measure of an intermediate output of innovation processes. Both have their strengths and weaknesses which need not to be discussed in detail here. The main problems with patents arise from the fact that not all inventions will be patented. Imitative and incremental innovations are not covered by patent statistics although they represent a large and increasingly important part of innovation activities of firms. The most obvious short-coming of R&D statistics is their undercoverage of innovation activities in small firms (see e.g. Kleinknecht and Reijnen 1991).[1] As recent research has shown small firms are less likely to be engaged in R&D; but if they have decided to do so, small firms invest more compared to their size than medium sized firms but less than large firms.[2]

It is well known from patent application data that a large share of patents is applied for by only a small number of firms and that, therefore, the distribution patent application numbers is highly skewed. But it is less known about the distribution of patenting or not by firm size. Figure 1 contains the size distribution of innovating, R&D performing and patenting firms. As expected, the percentages of innovating, R&D performing and patenting firms increase strongly with firm size. Slightly more than 50% of all manufacturing companies with more than 4 and less than 50 employees have introduced improved or new products or processes in 1990-1992 or intended to do so in 1993-1995.[3] The share of R&D performing firms amounts to 20% of all firms in this size class. However, just one out of ten innovating firms applies for a patent in 1992 in the smallest size class. In the largest size class the percentage of patenting firms exceeds 65%. When looking at the innovative firm only, the figure demonstrates that the shares of non R&D performing and non patenting companies decline with firm size. Thus the innovation activities of small and medium companies will most certainly be underestimated if only R&D and patents are used as indicators for innovative activities.

The difference between small and large firms is even more pronounced with respect to patent applications at more than one patent office in one year. The overwhelming majority of German patenting firms apply to the German patent office. Just around 10% of the patenting firms use the European procedure only and do not apply to the German office. The share of firms that do not only apply to the German or European patent office but also to the US Patent and Trademark Office or another patent office is increasing with firm size for small and medium sized firms. But this share is nearly constant for firms with more than 250 employees.[4] Since the application

1 Throughout the paper R&D always refers to the FRASCATI-definition (see OECD 1993).

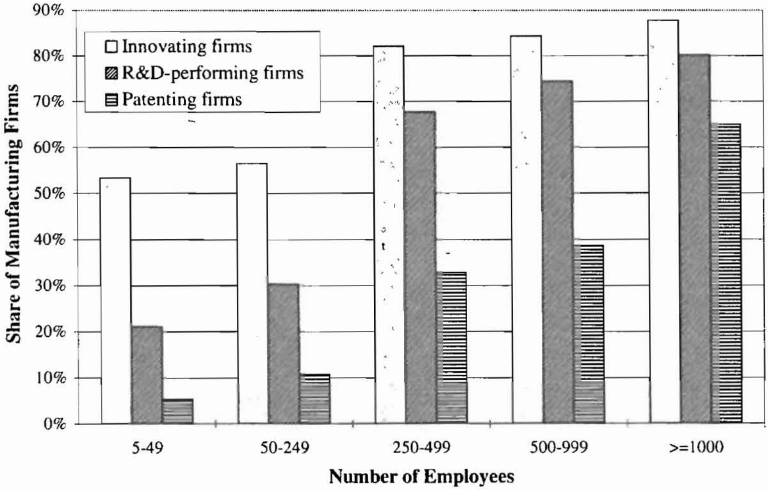
2 See e.g. Felder et al. (1996) who simultaneously model the decision to perform R&D and the R&D intensity. The U-shaped form of the relationship between R&D intensity and firm size depends strongly on the indicators used to measure R&D intensity.

3 These firms are called 'innovating companies'. Our definition of innovation takes a purely firm-specific view. So innovation comprise absolutely new products as well as new products which are pure imitations. Our questionnaire assumes that all companies which do not innovate within this six-year-period do not perform R&D in 1992 and do not apply for a patent in 1992.

4 The European patent procedure is rather expensive (e.g. patent fees; cost of translating the patent documentation into the languages of the destination countries). As a rule the European patent procedure is cheaper than the direct application via national patent offices if one seeks

cost at a foreign patent office are larger than a patent application at the home office, and exporting is more common in larger enterprises, this result is in line with our expectations. Our data produces two stylised facts already shown by Sirilli (1987) for the Italian manufacturing sector: the structure of international patenting activities is similar to the structure of international trade; abroad extension of patents is increasing with firm size. So, firm size and export status are expected to be important determinants of patent behaviour in foreign countries.

Figure 1: Innovating, R&D-performing and Patenting Companies in German Manufacturing Industries in 1992 - Weighted Data



Source: ZEW: Mannheim Innovation Panel (1995)

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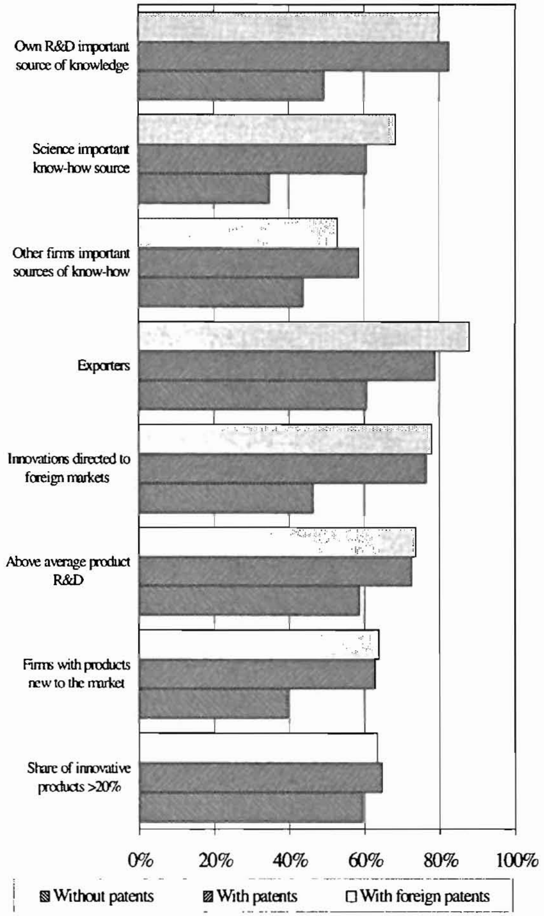
patent protection in more than three European countries. Therefore, we consider applications at the European Patent Office as abroad applications.

Patent strategies of firms maybe strongly depending on firm characteristics. This holds especially for application at different patent offices. But patent statistics lack information even on basic informations on firms applying for a patent. Therefore, not much is known with regard to differences in the characteristics between patenting and non patenting firms. So, we first look at the role of various attributes of the innovation process and firm characteristics for patenting and non patenting firms. Figure 2 documents some differences between non patenting firms, firms which apply for patents in Germany only as well as firms, which apply for patents at least to one foreign patent office. There are significant differences between patenting and non-patenting firms. But these differences are less significant between firms which only use GPO applications and firms which also apply to foreign patent offices (including EPO).

Figure 2: Innovation activities and patent applications in Germany 1992



Source: ZEW: Mannheim Innovation Panel (1995)

The first three items in Figure 2 relate to the sources of knowledge used to generate innovations. We distinguish (1) the firm's own R&D department, (2) scientific institutions and (3) other firms as being an important sources of know-how.[5] Own R&D seems to be an important source of know-how especally for patenting firms. A much larger share of patentors regard scientific institutions as an important source of knowledge for innovation processes. This difference is less pronounced with regard to private firms as sources of know-how. To fulfill the novelty requirements patenting firms show a more systematic, R&D based approach to knowledge generation than non patenting firms. These differences on the input side of innovation processes is also confirmed by differences with respect to the results of innovation processes. Figure 2 shows that a larger share of patenting firms introduced products which are not only new to the firm but represent market innovations. When we look at the share of sales of innovative products[6], we find no difference between patenting and non patenting firms. So, market success with innovative products not only depends on successful technological solutions which are represented by a patent, but also on complementary assets and activities of firms (e.g. superior sales effort).[7] In addition, Figure 2 shows that a lot of firms (40%) introduce products 'new to the industry' without applying for patent protection. One of the most prominent explanations maintains that patents are an imperfect tool for protecting innovations. Alternatively, market novelties do not always meet the novelty requirements of patents.

Furthermore, patenting firms spend a larger share of the total R&D budget than non patenting firms on product innovation. Those in turn spend a larger share on process R&D. But this does not imply that patentors devote a higher share of their total innovative activities to new products compared to non patenting companies. Cost saving process innovations and the generation and market introduction of product innovations are viewed as equally important by patenting and non-patenting firms. Figure 2 also shows that patents are an important tool in the strategy of firms. This notion rests on the result that exporting companies and companies with innovative activities devoted to foreign markets, are involved in patenting to a larger extent. This is even true when we look at patenting only in Germany. So, patenting seems to be especially important in markets which are open to international competition.

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5 'Scientific institutions' and 'other private firms' are 'aggregated' representations of various sources of information (e.g. customers, suppliers, competitors, consultants, universities, government research laboratories). Firms rate the importance of these source for innovation on a five-point scale. The aggregate values are the weighted sum of the scores given to these sources. Weights are obtained by a factor analysis (see Felder et al. 1996 for details).

6 'Innovative products' refer to products introduced to the market in the last three years. Innovative products are defined as 'new to the firm'. Therefore, this figure also includes the market success with pure imitative products.

7 Similar results are reported for France by Kabla (1996).

Protecting the home market by patents is only the first step in gaining intellectual property rights for new products at the world market.

3 A Theoretical Framework for the Econometric Analysis of Patent Applications

A firm will apply for patent protection if the expected marginal return of protection exceeds the cost of an application. The returns from using the patent system depend on whether patents are effective in preventing imitation by competitors. In addition, if competitors profit from the knowledge diffused through publication of patents returns are also adversely affected. Recently, Cohen et al. (1996) provide some evidence that patents are a rather imperfect shelter from imitation. As the theoretical models of Horstman et al. (1985) and Harter (1993) show, firms will not always apply for a patent if patents diffuse information to competitors. In order to protect its competitive edge, a firm may apply for patent protection for only some fraction of its inventions. Indeed, many firms may not rely on patents at all but on alternative mechanisms like secrecy or complexity of product design. Both arguments lead to the concept of the propensity to patent which states that firms patent only a fraction of their inventions. This is captured by the equation

(1) $P_{ij} = g_j(X_i)\, I_i$.

where P_{ij} is the number of patent applications of firm i at the patent office j. The vector X_i captures characteristics of firms which affect the difference between the marginal expected return from using patents and the costs for applying and holding of a patent. I_i is the number of inventions of firm i which fulfill the novelty test.

The function g represents the propensity to patent and depends on the characteristics of the patent system. The model of Horstman et al. (1985) implies g_j to be smaller than unity. In addition, as the application for patents at a foreign patent office is more expensive than an application at the home office we also suppose that on average foreign patents should be more valuable than patent application in the home country. So, the expected value of the least valuable patent applied for at a foreign office should exceed the least valuable patent at the home office. Therefore, we should keep in mind that patent applications at foreign offices may be more homogenous w.r.t. to their value than patents applied for at the home patent office.

Equation (1) can not be implemented directly as we do not observe the number of inventions at the firm level. But inventions can be viewed as the outcome of a systematic search process for novelties. The relationship between the outcome of innovative activities and the inputs can be represented by the concept of a production function for inventions. This analytical tool is thought to describe the transformation of R&D into new knowledge which in later stages of the innovation process is used for the development of new products and processes. We assume R&D to be the most important input into the knowledge generating process. In addition, firms profit from other firms' R&D. So, the larger this spillover is the larger will be the productivity of a firm to generate inventions. To capture this, we assume that R&D capital of the industry enhance the knowledge generating process of firms. Therefore, a simple version of the invention production function is given by

(2) $I_i = f(K_i, K_s, A_i)$

where I_i represents the number of inventions made by firm i in the period under consideration. K_i denotes the firm's own R&D capital and K_s indicates the R&D capital of all other firms (= the industry) from which knowledge spillovers arise. A_i represents other firm-specific factors which influence the R&D productivity of a firm in generating inventions. This factors are referred to as technological opportunities in the literature.

Combining (1) and (2) we derive an equation which relates the number of patents to R&D and various factors which influence the propensity to patent.

(3) $P_{ij} = g_j(X_i)\ f(K_i, K_s, A_i)$

To keep the model as simple as possible, we assume that g_j and f are exponential functions of a linear combination of their arguments. Therefore, the log of the number of patents is modelled as a linear function of the arguments of g and f. Given the nature of invention, a random error uncorrelated with the arguments of g and f is added to the loglinear version of equation (3). This random error should also account for unobserved heterogeneity due to the economic value of an invention. As firms probably differ in their ability to assess a priori the economic value of an invention and hence of a patent,[8] their propensity to patent might be affected by this unobserved ability.

Equation (3) relates the number of patent applications to R&D in a rather simple manner but also shows that there probably is a number of other variables intervening into the relationship between R&D and patents. Spillovers have an ambigious effect on the number of patents. On the one hand spillovers will enhance the productivity of R&D and increase the number of inventions. On the other hand spillovers probably reduce the propensity to patent and induce firms to rely on alternative mechanisms to protect the competitive edge. In addition, if patents induce an overinvestment in R&D it can occure that we observe a negative correlation between industry's R&D and the number of patents.

[8] It is well-known from the literature that the economic value of patents differs widely (see Lanjouw, Pakes and Putnam 1996 for a survey).

4 Empirical Implementation

Our data set contains information on the number of patent applications at the German, the European and US Patent Office by German firms in 1992. Unfortunately, we do not observe whether this patent applications refer to the same invention, d.i. belonging to the same patent family. Moreover, given the rules of international patenting, it seems not reasonable to assume that this is the case. Extentions of patent applications at the home office to foreign patent systems usually do not occur within the same year.

We are restricted to a single cross-section of data which implies that the cost of patent applications does not vary very much in the sample used. Variation in application costs is mainly present between offices. E.g. it is well-known that patent applications at the European patent office are far more expensive than patent applications at the German office. So, we should expect that firms apply for patent protection for some of the less valuable inventions at the German patent office but hesitate to apply for this invention at the EPO or foreign patent offices. Therefore, patent applications at foreign patent offices are expected to have a large mean economic value when compared to the patent application at the home patent office. So, differences in application costs and the value of patents are given only implicitly as our data set contains patent applications at different patent offices. We should keep this in mind when we interpret the estimation results.

The implementation of various exogenous variables also need some further comments.[9] Since our data set does not contain any information on past R&D expenditure which would allow the construction of firm specific R&D capital stocks, we use the current R&D expenditures as a proxy for the R&D capital stock. But our data allow us to identify whether a firm performs R&D on a continuous basis. This information can be used to account for past R&D, which has a long-lasting effect on the productivity in generating patents.

The construction of the spillover pool is also restricted by data availability. Since no information is available on the technological field (e.g. Jaffe 1988) or the product groups (e.g. Harhoff 1994) in which firms perform R&D, we use the total R&D expenditures of an industry as reported in the official 1992 German R&D statistics (see SV-Wissenschaftsstatistik 1994). In addition, we account for firm specific differences in the invention production function. Following Levin and Reiss (1987) we assume that the productivity is higher because of higher technological opportunities if firms view scientific sources as an important source of information for their innovation activities.

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[9] The definitions of the variables are summarized in Table 1. Descriptive statistics by firm size are given in the Appendix 1.

Table 1: Definition of variables

Variable name	Short description
PATENT MEASURES	
PATDE	No. of patent applications at German Patent Office
PATEU	No. of patent applications at European Patent Office
PATUS	No. of patent applications at US Patent and Trademark Office
EXPENDITURES FOR R&D	
LR&D:	R&D expenditures in 1992 (in DM 1000; in logs)
LR&DSQ	R&D expenditures in 1992 (in DM 1000; in logs) squared
PERM_R&D	Dummy for firms with permanent R&D activities
SPILLOVER MEASURES	
SPILL	Spillover pool=Total R&D of industry (in Mill. DM; in logs)
R&D_SPILL	Spillover pool multiplied by the firms' own R&D (in logs)
FIRM SPECIFIC PRODUCTIVITY INDICATORS	
SCIENCE	Importance of scientific institutions as source of knowledge for innovations (factor analysis; see Felder et al. (1996)
OTHFIRM	Importance of other firms as source of knowledge for innovations (factor analysis; see Felder et al. (1996)
EXPORT STATUS	
EX_SHARE	Export share
EXPORT	Dummy for exporting firm
EX_PLAN	Innovation activities planned for the US, Japanese or other overseas market (Dummy: 1= important or very important)
FIRM SIZE	
LEMP	Number of employees (in logs)
OTHER FIRM CHARACTERISTICS	
EAST	Firm in East-Germany
DIVERS	Degree of diversification calculated as the inverse of the sum of squared sales shares (%) for the 4 major product groups. Therefore a single product firm will have the value 1.
FOREIGN	Foreign subsidiary
GROUP	Part of a group

Firm size probably affects the marginal costs of patent application. As many small firms neither have a specialised unit dealing with patents or property rights nor detailed prior information about the patent system, their costs per application are expected to be higher than the marginal application costs of large firms. Zimmermann und Schwalbach (1991) show that the number of patents strictly increases with firm size. In addition, it is often argued that small firms hesitate to apply for a patent because of the large patent litigation costs. We test for the effect of firm size on the propensity to patent by including the logarithm of the number of employees.

Several studies argue that the degree of diversification has an impact on the propensity to patent (see e.g. Zimmermann and Schwalbach 1991). The reason for this behaviour is that more diversified firms may use an invention in different products and processes. So the market risk of innovation is lower and the expected marginal returns from patenting are higher.

We consider the impact of the export status of a firm on the propensity to patent. A positive impact of exports on the propensity to patent is expected as the number of competitors gets larger for exporting firms and, therefore, protection of knowledge is more important.

Due to the transformation process in East-Germany, the productivity in generating patents as well as the propensity to patent are likely lower among East-German than among West-German companies. This is most obvious from the fact that within a few years, the number of R&D personnel drops from 88 000 (1989) to around 22 000 (1993). This drop is accompanied by reorganisations of R&D departments. In addition, new R&D projects are started recently have less in common with R&D programmes of the former GDR enterprises which were to a large extent imitation of Western technologies. Therefore, a dummy for East-German firms is included.

Finally, the propensity to patent as well as the patent productivity are affected by other firm characteristics. In some firm groups only the mother company applies for the patent regardless of the subsidiary brought forth the invention. This is especially well known from foreign companies. On the other hand daughter companies might profit from R&D performed in other parts of the group which would imply a higher productivity of the observed unit. Therefore, we use dummies for firms which are part of the group and for firms with a foreign mother company.

5 Econometric Modelling

The number of patents is restricted by definition to non-negative integers. Appropriate estimation techniques for this kind of data are given by the family of count data models. Count data models are applied to the patents-R&D relationship by a number of researchers including Bound et al. (1984) as well as Hausman, Hall and Griliches (1984) for the US, Crépon and Duguet (1993) for France or Zimmermann and Schwalbach (1991) for Germany. Our econometric modelling strategy starts with some basic models for count data which we describe briefly in the first part of the chapter. The second part of this chapter deals with hurdle models for count data.[10]

The economic rationale for applying hurdle models rest on the plausible assumption that the decision to apply for the first patent and the decision to apply for additional patents are ruled by different processes. The decision to apply for a patent has to be made when the yield of holding this patent is not known exactly. Firms often adopt some basic decisions how to protect intellectual property and how to handle patentable inventions. This basic decision is often made in the context of the first invention. The decision to apply for patents for additional inventions is often based on this first principle decision. So, we should expect different rules which govern the decision concerning for the first patent and for additional patents. The empirical specification of the model should take potentially different decision processes into account. Clearly, all firms included in our sample are assumed to decide whether to

[10] Appendix 3 contains an overview of various econometric tests for count data models and reports the results for the data set at hand.

patent their innovations or not. Therefore, we restrict the sample to those firms which actually introduced a product or a process innovation in recent years.[11]

Basic Models for Count Data

As a starting point it is often assummed that the data generating process follows a poisson distribution. If the random variable $Y_i \in \{0,1,2..\}$ is poisson distributed, the probability that exactly y_i counts are observed, is given by

$$(4) \quad P(Y_i = y_i|\lambda_i) = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!}, \qquad y_i = 0,1,2,... \qquad \text{with} \quad E[Y_i] = Var[Y_i] = \lambda_i > 0$$

Covariates can be introduced by specifying the individual mean by $\lambda_i = \exp(x_i'\beta)$ to ensure the positiveness of the mean. Here x_i' denotes a (1×k) vector of non-stochastic covariates of firm i and β is the corresponding coefficient vector. Assuming a random sample of individual observations (y_i, x_i), the vector β can be estimated by maximum likelihood methods.

In empirical work the equality of conditional mean and conditional variance of the distribution of the dependent variable, implied by the model, often turns out to be too restrictive. In most applications the conditional variance exceeds the conditional mean which is known as overdispersion. Overdispersion can have at least two distinct statistical sources: positive contagion (occurrences influence future occurences) or unobserved heterogeneity (see Winkelmann and Zimmermann 1995, McCullagh and Nelder 1989).

A first alternative are models assuming a negative binomial distribution for the data generating process. As shown in the literature, the negative binomial model is an extension of the standard poisson model where the poisson parameter for each firm λ_i has an additional random component, accounting for (unobserved) heterogeneity, not yet accounted for by the regressors that determine the individual mean function.

Specifying $\tilde{\lambda}_i = \exp(x_i'\beta + \varepsilon_i) = \exp(x_i'\beta)u_i$ where ε_i is an error term uncorrelated with the explanatory variables, captures unobserved heterogeneity and leads to a stochastic mean function with expectation $E[\tilde{\lambda}_i] = \lambda_i$ and variance $Var[\tilde{\lambda}_i] = \lambda_i^2\sigma_{u_i}^2$.The negative binomial distribution for Y_i results as a compound

[11] If there were firms that would not even think about patenting their innovations, the "zero inflated" count data model of Lambert (1992) would be a possible alternative. But this would not correctly model the propensity to patent that we have in mind. Lamberts model would only allow us to distinguish between firms that would never ever patent and others that follow a more conventional pattern comprising the number of patents as well as not to patent at all.

poisson distribution if the mixing distribution is the gamma distribution. Assuming ε_i to be gamma distributed or equivalently $\tilde{\lambda}_i \sim Gamma(\phi_i, v_i)$, one can derive the negative binomial distribution for Y_i with:

$$(5) \quad P(Y_i = y_i) = \frac{\Gamma(y_i + v_i)}{\Gamma(y_i + 1)\Gamma(v_i)} \left(\frac{v_i}{\phi_i + v_i}\right)^{v_i} \left(\frac{\phi_i}{\phi_i + v_i}\right)^{y_i}$$

with expectation $E[Y_i] = \phi_i$ and variance $Var[Y_i] = \phi_i + v_i^{-1}\phi_i^2$.

Specifying the individual mean function as above, $E[Y_i] = \phi_i = \exp(x_i'\beta)$, we get the regression model with an unknown coefficient vector β and an unknown variance parameter v_i. Choosing different parametrisations for the precision parameter v_i allows to model different variance to mean ratios of the dependent variable. Setting $v_i = \alpha^{-1}$, a constant for all firms, leads to a model with the following form of heteroscedasticity: $Var[Y_i] = E[Y_i](1 + \alpha E[Y_i])$. The variance-mean relationship is linear in the mean. Following Cameron and Trivedi (1986), we call this the type II negative binomial model (negbin II). Similarly, a type I negative binomial model (negbin I) is obtained by setting $v_i = \alpha^{-1}\exp(x_i'\beta)$. The variance implied by negbin I can be written as $Var[Y_i] = (1 + \alpha)E[Y_i]$, with a constant variance-mean ratio. negbin I and II are different models and in general lead to different estimates for β.

Hurdle models for Count Data

A further alternative modelling strategy in the light of overdispersion is to assume that the decisions of whether or not to patent and to apply for more than one patent are ruled by different processes. This can be done using hurdle models for count data proposed by Mullahy (1986). The hurdle model takes account of the fact that there may be different distributions which govern the first decision to patent an invention and the decision to apply for patent protection for other inventions. In a more technical view, the hurdle specification rests on the assumption that the data generating process is driven by two sets of parameters. The underlying idea is that a binomial probability model governs the binary outcome of whether a count variate has a zero or a positive realisation (Mullahy 1986). Once the hurdle is crossed and positive counts are observed, the data generating process is governed by a truncated-at-zero count model. The binomial process in the first stage can also be interpreted as a threshold-crossing binary choice model, in which the continuous latent variable is the firm's propensity to enter the second stage of the process, i.e. the firm's willingness to patent an invention (see Pohlmeier and Ulrich 1995).

Assume that f_1 is any probability distribution function for non-negative integers, that governs the decision whether or not to patent, and that f_2 represents the process governing the decision once the hurdle is crossed. Then the probability distribution of the model is given by:

$$(6)\quad \begin{aligned} &P(Y_i = 0) = f_1(0) \\ &P(Y_i = y) = (1 - f_1(0))\frac{f_2(y)}{1 - f_2(0)} \end{aligned}$$

$(1 - f_1(0))$ gives the probability of crossing the hurdle and $(1 - f_2(0))$ is the normalisation for $f_2(y)$ because of the truncation at zero (see Winkelmann and Zimmermann 1995).

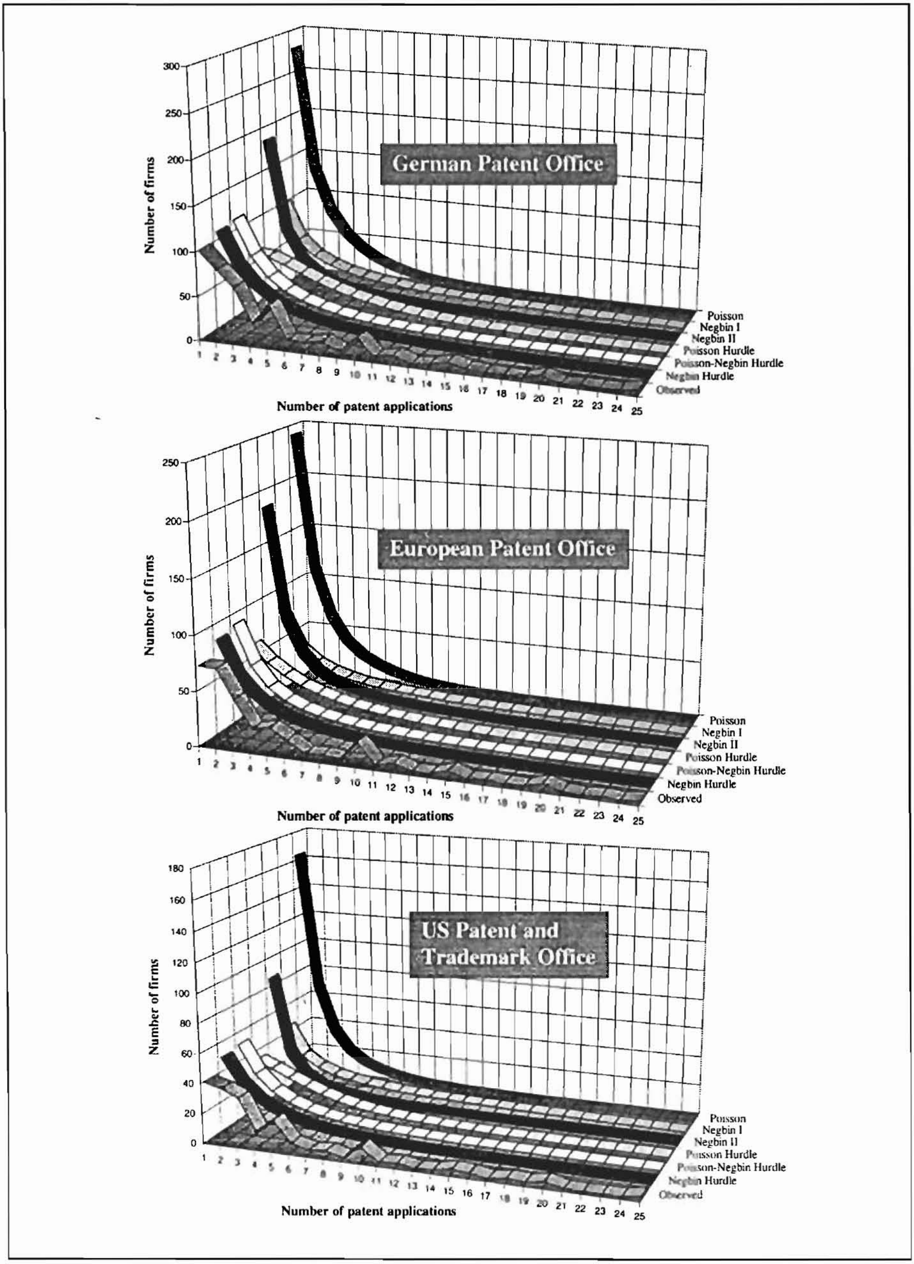
The likelihood of the model depends on two different parameter vectors: β_1 represents the parameters w.r.t. the decision for the first patent, β_2 captures the parameter vector which refers to the decision to apply for more than one patent. Let Ω_0 denote the subsample of firms without a patent application and Ω_1 represents the subsample of firms with at least one patent application. Then we can write the likelihood as follows:

$$(7)\quad L = \prod_{i \in \Omega_0} P(Y_i = 0 | x_i'\beta_1, \alpha_1) \prod_{i \in \Omega_1} [1 - P(Y_i = 0 | x_i'\beta_1, \alpha_1)] \prod_{i \in \Omega_1} \frac{P(Y_i = y_i | x_i'\beta_2, \alpha_2)}{1 - P(Y_i = 0 | x_i'\beta_2, \alpha_2)}$$

The likelihood for the binary process to patent or not to patent is given by the first two expressions (7), and the last part is the likelihood of a truncated-at-zero count model.

We chose negbin II as the underlying distribution for both stages for the following reasons: It captures unobserved heterogeneity, allows for overdispersion in its own right and enables us to test the distributional assumptions. In addition, we estimate the poisson hurdle model proposed by Mullahy (1986), where we assume that the underlying distribution for both stages is poisson. Finally, we also consider a poisson-negbin hurdle model which assumes the poisson distribution for the first stage and the negbin II distribution for the second stage.

Figure 3: Comparison of Observed and Predicted Counts for Various Count Data Models



Moreover, our hurdle models comprise the conventional count data models as special cases. If the parameter estimates for both stages are the same the negbin hurdle model as well as the poisson hurdle model collapse to the underlying conventional model (negbin II model in the case of the negbin hurdle model and poisson model in the case of the poisson hurdle model). Furthermore, it can be shown that if the overdispersion parameter converges to zero, $\alpha \rightarrow 0$, the negative binomial distribution collapses to the poisson distribution. Within the negbin hurdle specification we obtain the poisson-negbin hurdle model if $\alpha_1 = 0$ and poisson hurdle model if $\alpha_1 = \alpha_2 = 0$[12] (see Pohlmeier and Ulrich 1995). Hence, it is quite easy to test the various models against each other. More details can be found in Appendix 3.

As stands out from Appendix 3, our test strategy implies that a negbin hurdle model is preferable. Moreover, this conclusion is confirmed by comparing the observed number of firms with a certain number of patents and the predicted number of firms with a given number of patent applications. These predictions are obtained by first calculating for each observation, the probability for a certain number of patents and then by summing over these individual predicted probabilities for each category (see Winkelmann and Zimmermann 1995). The predicted and observed number of firms within each category (number of patents) are compared in Figure 3, details are reported in the Appendix 4. We will thus report only the results from the negbin hurdle model, noting that the results for the alternative poisson negbin hurdle model are rather similar.

6 Regression Results

Regression results for the model outlined in equation (7) are reported in Table 2.[13] The model is estimated separately for patent applications at the German, the European and the US patent office. Overall, we find remarkable differences between patent applications at the German Patent Office, the European Patent Office, and the US Patent and Trademark Office. In our opinion this partly reflects peculiarities of the patent procedures of these three offices and can be attributted to the smaller heterogeneity of patents in terms of their value in the case of the EPO and USPTO.

But the results demonstrate that the patent strategies of firms are important determinants of patent activities and, therefore, the number of patents produced by an economy in a given year not only reflects technological success but also depends on behavioural patterns of firms. The number of patents of a firm rests not only on

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[12] α_1 denotes the overdispersion parameter for the hurdle stage, α_2 for the second stage when the hurdle is crossed.

[13] STATA, Version 4.0 is used for estimation.

the productivity in generating invention but also on their propensity to patent. This can be seen in the differences of estimated parameter vector for the decision stage and the number of patent part of the hurdle models. Different parameter vectors for both stages are evident from the specification tests reported in Appendix 3.

In addition, the propensity to patent not only affects the decision whether to patent or not, but also affects the number of patents. This is evident from the fact that export share and firm size which were expected to be arguments of the propensity to patent part of the model, are also significant in the second stage. This interpretation is also confirmed by the parameter estimates for the diversification indicator: the higher the degree of diversification the lower will be the number of patents applied for. But the principal decision on whether or not to patent is unaffect by diversification. A possible interpretation of this result could be that diversified firms spend a larger share of their R&D on incremental, non-patentable innovations, so that their 'productivity' in generating patents is lower.

R&D turns out to be a major source in generating new knowledge. The elasticity of the number of patents with respect to R&D is increasing with current R&D expenditures as it is indicated by the coefficients of log R&D (LR&D) and its square (LR&DSQ) in the patent numbers part of the model. Our results, therefore, suggest economies of scale with respect to the production of patents. Figure 4 shows the elasticities of the number of patents applied for with respect to R&D. The elasticities are increasing throughout the relevant range of R&D expenditures.

Besides the R&D elasticity of patent numbers, Figure 4 indicates the median value of firms R&D expenditure for those firms which apply to the three patent offices. These calculations show that for the median R&D performer the elasticity is rather close to one. Only for some large R&D spenders, economies to scale are sufficiently large. So, for the majority of firms our results do not deviate too much from recent results for France by Crépon and Duguet (1996) who find an elasticity of patent w.r.t. R&D not deviating significantly from unity.

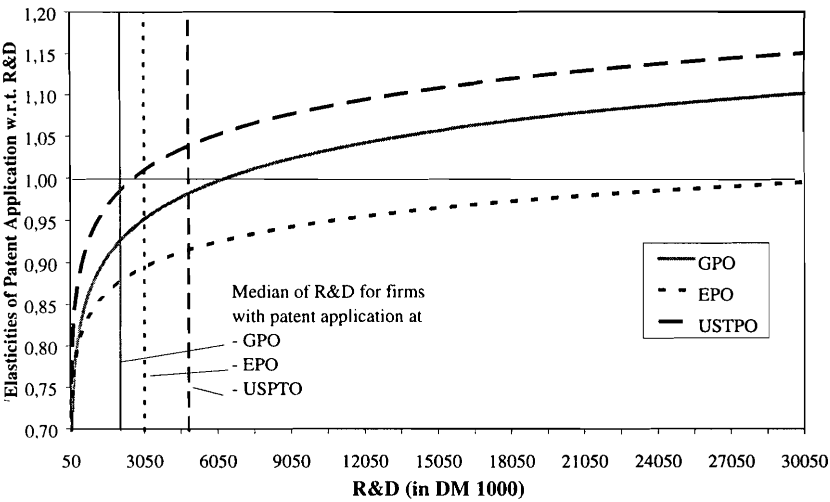
Moreover, different fixed costs seem to be associated with patent applications at the GPO, the EPO and the USPTO. The parameter estimates for R&D in the hurdle stage is much lower for the GPO than for the EPO and the USPTO. The parameter estimates for the second stage of the hurdle model are far less different between these different kinds of patent applications.

Table 2: Patent Applications at the German Patent Office, European Patent Office and the US Patent and Trademark Office - Results for the Negbin Hurdle Regression Model

	German Patent Office				European Patent Office				US Patent and Trademark Office			
Summary statistics												
Observations	1685				1689				1694			
Log.Likelihood	-1859.1				-1337.31				-828.18			
χ^2 / df / Pseudo R^2	1002.5		56	0.213	913.3		56	0.255	685.4		56	0.293
Exogenous Variables	**Decision part**		**Patent numbers**		**Decision part**		**Patent numbers**		**Decision part**		**Patent numbers**	
	Coeff.	**t-values**	**Coeff.**	**t-values**	**Coeff.**	**t-values**	**Coeff.**	**t-values**	**Coeff.**	**t-values**	**Coeff.**	**t-values**
LR&D	0.384	1.82	-0.013	-0.09	0.853	2.08	0.107	0.47	1.033	1.72	0.077	0.22
LR&D²	0.019	1.19	0.033	5.87	0.081	2.48	0.022	3.37	0.104	2.24	0.031	3.54
PERM_R&D	0.324	1.21	0.328	1.29	1.014	2.25	-0.302	-0.81	0.105	0.13	0.234	0.33
SPILL	-0.322	-0.62	-0.004	-0.01	-0.784	-0.79	-0.784	-1.44	-0.323	-0.24	-0.669	-1.10
R&D_SPILL	-0.003	-0.13	0.028	1.52	-0.006	-0.17	0.004	0.14	-0.013	-0.24	0.007	0.18
SCIENCE	0.222	2.00	0.199	2.83	0.207	1.20	0.316	3.54	0.544	1.82	0.108	0.95
OTHFIRM	0.135	1.25	0.001	0.01	0.071	0.40	0.068	0.71	-0.362	-1.23	0.101	0.89
EX_SHARE	0.713	1.62	0.550	2.02	2.089	2.54	0.699	2.02	3.969	2.64	1.250	2.73
EXPORTER	0.324	1.11	-0.051	-0.19	0.293	0.55	0.194	0.48	1.306	1.08	-0.578	-0.95
EX_PLAN	0.248	1.33	0.068	0.59	0.500	1.62	0.200	1.36	2.197	3.24	0.081	0.40
LEMP	0.311	3.41	0.351	5.95	0.273	1.82	0.401	5.37	0.356	1.67	0.318	3.34
LEMP * EAST	0.092	0.56	0.008	0.07	0.028	0.08	-0.394	-0.99	-1.154	-1.55	-0.655	-1.18
EAST	-1.458	-1.73	0.398	0.55	-3.025	-1.59	3.599	1.46	1.868	0.53	3.094	0.98
DIVERS	0.027	0.04	-0.923	-2.09	-0.653	-0.59	-0.474	-0.83	0.646	0.36	-1.205	-1.78
FOREIGN	-0.402	-1.13	-0.225	-1.03	-0.451	-0.77	-0.053	-0.21	-0.529	-0.63	0.081	0.26
GROUP	-0.120	-0.61	-0.088	-0.75	0.137	0.42	-0.129	-0.92	0.188	0.38	-0.257	-1.51
Industry dummies	included		included		included		included		included		included	
$\ln \alpha_1$, $\ln \alpha_2$	0.517	1.03	-0.117	-0.88	1.493	3.67	-0.064	-0.39	2.035	4.39	-0.281	-1.40
Constant	-1.001	-0.37	-0.958	-0.48	-0.061	-0.01	2.745	0.98	-4.725	-0.67	2.360	0.71

All models are estimated by maximum likelihood. The likelihood function is given by equation (7). The χ^2-value refers to a test against a model with constants as well as $\ln \alpha_1$ and $\ln \alpha_2$.

Figure 4: Elasticities of the number of patent applications w.r.t. R&D



Remark: Calculations are based on regression estimates reported in Table 2. We use the estimates of the 'numbers part' only. The value of the spillover-effect is evaluated at the median value for the GPO.

The evidence for positive knowledge spillovers from other firms R&D investment seems rather weak in our data. No significant impact of the spillover pool (SPILL) on patent activity is observed. Moreover, as the interaction term between own R&D and the spillover pool (R&D_SPILL) is not significant, we conclude that even in high-tech sectors the patent productivity is not affected by spillovers or patent rivalry effects. So, our results do not confirm Crépon and Duguet (1996) who find negative rivalry effects with regard to the number of patents of French companies. They also point out that this effect is especially important for big companies. As many small and medium firms are included in our data set this can be an explanation for this different results.

Technological opportunity should reflect interfirm differences in R&D productivity: Those firms which regard scientific institutions as primary sources of information for their innovation activities (SCIENCE) apply more often for patents. This reveals that the productivity of R&D is larger in technological areas where the know-how generating process within the firms is enhanced by ongoing research in public scientific infrastructure.

Export activities seem to be one of the major determinants of a firm's propensity to patent. Even in the case of applications at the GPO, the number of patent applications increases with the export share. As one would expect, the effect of exports increases when looking at the EPO and even more when looking at the

USPTO. This is even more pronounced if innovation activities are undertaken to protect future competitiveness in foreign markets.

Firm size exhibits a large effect on patenting. The propensity to patent seems to increase with firm size. Even more surprising is the large firm size effect found in the patent numbers part of our model. This can be interpreted towards a higher productivity in generating invention in large firms. An alternative explanation could be that rules, adopted in larger firms, stimulate patent applications even if the economic value of an invention is probably low.[14] Moreover, larger firms are probably more aware of the role played by patents in cross-licensing agreements, R&D cooperations and the strategic dimension of patents. Legal regulations like the German Employee Inventor Law („Arbeitnehmererfindergesetz“) also stimulate to patent applications. Those rules are probably more important considerations for the formalised innovation processes of large companies and, therefore, in line with the increasing propensity to patent in large companies.

We should also note that despite of a large correlation of firm size and R&D in a cross-section regression, the coefficients on the R&D variables only slightly change when we drop firm size from our regression.

Other firm characteristics included in the model are some what surprising. We do not find a significant negative effect neither for small nor for large East-German firms. Only in the hurdle stage in the regression model for the German patent office the East-German dummy variable nearly reaches statistically significance. So, our model do not point to a lower patent productivity nor to a different behaviour towards patents in East-German firms. The small patent numbers of the East-German economy are mainly caused by a low R&D effort and the small number of large firms in East-Germany.

In addition, our expectations with regard to a lower patent activity of group members and subsidiaries of foreign firms are not fulfilled by our results. Given the large differences in the way multinational companies organize their decision processes a more refined modelling seems to be necessary before we can reach more clear-cut conclusions with regard to the patent behaviour of the German daughters of multinational companies.

Finally, our specification also includes 12 sector dummies. We omit the discussion of these dummies because it is difficult to interpret whether they reflect interfirm differences in the propensity to patent or in the invention production function.

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[14] Giese and Stoutz show that patent applications of large firms are less probably lead to patent grants.

7 Summary and some hints on further research

Based on the data of the first wave of the Mannheim Innovation Panel, this paper explores the role of patents as appropriability mechanisms and the relation between R&D expenditures and patents. This data generates the possibility to look at the firm size distribution of patents application at different patent offices.

Before summarizing the main results, some qualifying remarks are in order. First, as it is shown by various other studies (see e.g. Harhoff 1994 for German manufacturing) spillovers and appropriability conditions depend crucially on the nature of technology. Further research should more explicitly explore the possibility to estimate our model for high-tech and low-tech sectors separately. Secondly, we neglect technology-specific effects. These effects can be accounted when using the information on technology inherent in the classification of patents by patent office. Therefore, we should seek to explicitly merge available patent application data at the level of patents to our firm level data set (see e.g. Jaffe 1989). Finally, R&D expenditures and patent applications are maybe determined simultaneously (see Pakes 1985). Future research should try to take this simultaneity into account and test whether the results of this paper suffer from a simultaneous equation bias.

The results of the paper can be summarized in the following way: In the first part of the paper it is shown that the share of R&D performing firms strictly increases with firm size. The share of firms applying for patents exhibits an even steeper increase with firm size. Moreover, the larger a firm, the more likely it is to apply for patents in more than one country. Although large firms apply for a German patent with a higher probability than SMEs, large firms also apply to the European patent office whereas SMEs often apply for a patent at the German patent office only. The German patent office seems to be especially important for small firms.

The second part of the paper explores the relationship between R&D and patents more closely. We find a close relationship between R&D and patents. Our hurdle negbin regression model implies the presence of economies of scale in the patents-R&D relationship. But the elasticity of patents with respect to R&D significantly exceeds unity only for large R&D spenders. For the majority of firms this elasticity is just around 1. Using the R&D expenditures of the industry, our model is thought to capture spillovers or effects of R&D rivalry on the number of patents. But we failed to find empirical evidence for these effects.

Even after controlling for a variety of firm characteristics, firm size exhibits a large effect on the propensity to patent. Patents also play an important role when looking at export strategies of firms. Exporting firms apply more often for patents at the German patent office and even more at foreign patent offices. Therefore, we should be very careful when using patent numbers as an indicator of the technological capabilities of firms or economies as strategic decisions are important determinants of the number of patent applications. So, a change in the number of patents applications of an economy in a given year can well be the result of a change in the patent strategy of firms and need not to be the result of an increase in the technological capabilities of the economy.

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Appendix 1: Description of the Data Set

Data were taken from the first wave of the Mannheim Innovation Panel. This multi-year innovation survey has been conducted by the 'Zentrum für Europäische Wirtschaftsforschung' (ZEW) and the 'Institut für angewandte Sozialforschung' (infas) since 1993. The sampling frame stems from the records of Germany's largest credit rating company (CREDITREFORM). The sample was stratified by industries and firm size classes as well as West- and East-Germany. The questionnaire follows the guidelines for innovation statistics contained in the OSLO-manual of the OECD (see OECD 1997). Moreover, it is based on the harmonised questionnaire for innovation surveys developed by EUROSTAT. In addition to the harmonised questionnaire, our survey also contains information on patent applications. Firms are asked whether they have applied for patents at German, European, US patent offices and to estimate the number of patent applications made at each office. Furthermore, the questionnaire covers a broad range of topics related to the innovation process, such as the objectives behind innovation activities, the obstacles that firms encounter in this connection, characteristics of the knwo-how generating process, mechanisms for protecting technological knowledge, and firm's expenditure on innovation activities (including R&D).

Approximately 2900 companies participated in the survey and completed the questionnaire. The response rate was about 24%. The survey covers innovative as well as non-innovative firms. An innovative company is defined as a firm which introduced at least one new or improved product or process in 1990-1992 or intended to do so in 1993-1995. To account for a possible bias arising from self-selection of innovative firms into the survey, we conducted a short telephone survey of non-respondents of the initial survey. This telephone survey provided basic information on additional 1000 firms. The non-response survey yielded a response rate of nearly 90% which makes a response bias in the survey rather unlikely. Based on data from the original survey, the sampling frame, and the telephone survey of non-respondents, we use probit models to estimate the participation probability in the original survey. It turned out that innovating and R&D performing firms participate in the survey with a higher probability. Therefore, analyses based only on respondents may be biased as non-R&D performing firms and non-innovators are underrepresented in the sample.

The descriptive statistical analysis contained in chapter 2 of this paper is based on weighted data. To correct for response bias, we calculate the individual weights for the responding firms as follows: Let the inclusion probability for the firms of strata j be denoted by z_j and the participation probability for firm i by r_i , which is estimated by a Probit-regression model including firm size, industry affiliation, a credit rating indicator, as well as dummies for R&D and innovation activities as regressors. Weighting factors correcting for the non-response bias are then calculated as $w_i = 1/(z_j\ r_i)$ i.e. raising factors are given by the inverse of the inclusion probability multiplied by the inverse of the participation probability. Weighted data are, therefore, less likely subjected to a response bias in favour of innovative and R&D performing firms (for further details see Harhoff, Licht et al. 1996).

About 35% of the firms in our sample belong to the group of non-innovating companies. With exception of chapter 2, we restrict our analysis to the group of innovative firms. Furthermore, we delete all service sector firms since their questionnaire contains no information on patents. Overall, data of about 2100 firms are included in this study[15].

[15] The largest enterprises in the sample were split into lines of businesses. We refer to these entities in this paper as firms too.

Appendix 2: Descriptive Statistics by Firm Size for Data Used in Regression Analysis - Unweighted Data

VARIABLE	Enterprises with less than 250 employees		Enterprises with 250 employees and more	
	Mean	Std.dev.	Mean	Std.dev.
Share of patenting firms	0.152		0.538	
Firms with patent application at GPO	0.127		0.480	
Number of patent applications at GPO	0.388	1.966	7.291	35.004
Firms with patent applications a USPO	0.029		0.230	
Number of applications for US patents	0.078	0.592	4.152	45.657
LR&D	-4.049	2.864	-0.432	3.462
PERM_R&D	0.468		0.801	
SPILL	7.473	1.501	7.701	1.528
R&D_SPILL	-29.219	21.518	-1.400	25.739
SCIENCE	-0.193	0.869	0.288	0.836
OTHFIRM	0.047	0.811	-0.059	0.816
EX_SHARE	0.131	0.194	0.286	0.240
EXPORT	0.609		0.887	
EX-PLAN	0.236	0.425	0.440	0.497
LEMP	3.883	1.029	6.754	1.055
LEMPO	1.691	2.011	1.033	2.394
EAST	0.443		0.160	
DIVERS	1.968	0.942	2.240	1.443
FOREIGN	0.022		0.099	
GROUP	0.166		0.532	
Industries				
Mining. Energy	0.022		0.038	
Food. tobacco	0.092		0.078	
Paper. Pulp. Printing. Wood processing	0.099		0.057	
Chemical industries. refineries	0.071		0.104	
Plastics. rubber	0.075		0.037	
Earth. ceramics	0.042		0.037	
Steal. iron. basic metalls	0.028		0.050	
Metal working	0.109		0.078	
Mechanical engineering	0.207		0.250	
Electrical engineering. computers	0.080		0.083	
Optics. precision instrumentes	0.085		0.069	
Transport equipment (cars. railroads etc.)	0.053		0.069	
Construction	0.038		0.050	

Appendix 3: Model Selection and Testing the Distributional Assumptions For Count Data Models

Count data models assume a dependent variable resulting from an underlying discrete probability function. The econometric toolbox offers a wide range of possible distributional assumptions. This appendix describes our procedure to test these distributional assumptions and to select the most appropriate empirical specification. We restrict ourselves to the poisson distribution and compounds of the poisson distribution. The results are summarized in Figure A1.

As mentioned above several of the models are nested. Testing in this case is done using likelihood ratio tests as well as Hausman tests if applicable. The Hausman test is not applicable to test the negbin models against the poisson model since the poisson and the negbin models (for any fixed value of α)[16] belong to the linear exponential family, which implies consistent pseudo maximum likelihood estimates of the mean function both under the null and the alternative hypothesis. This is not the context in which the Hausman test can be applied. For $H_0{:}\alpha = 0$ the true parameter is on the boundary of the parameter space. The asymptotic normality property of the ML estimator does not hold and the conventional LR-, LM- and Wald-tests cannot be applied. However, Chernoff (1954) shows that under the null hypothesis the likelihood-ratio statistic for testing $\alpha = 0$ is similar to a random variable which has a probability mass of 0.5 at zero and a $0{,}5\chi^2(1)$ distribution for positive values (see Lawless 1987, Winkelmann and Zimmermann 1995). We used this property to test the negbin models (I and II) against the poisson model. This idea is also applied to test the poisson-negbin hurdle model against the poisson hurdle specification and also to test the negbin hurdle specification against the poisson-negbin hurdle specification.

If the models at hand are not nested we apply a likelihood ratio based test for strictly non-nested models proposed by Vuong (1989). Using the Kullback Leibler Information Criterion to measure the closeness of a model to the truth, Vuong devices a likelihood-ratio based statistic for testing the null hypothesis that the competing models are equally close to the true data generating process against the alternative hypothesis that one model is closer.

We start with testing the basic models discussed in Chapter 5. First, we test the poisson model which implies the equality of conditional mean and conditional variance of the distribution of the dependent variable. In most applications the conditional variance exceeds the conditional mean which is known as overdispersion. We test for overdispersion using regression-based tests of Cameron and Trivedi (1990). This is done with the help of a standard t-test from an auxilliary regression which is asymmtotically equivalent to their optimal test.[17] This test is computed from an OLS regression of $(\sqrt{2\lambda_i})^{-1}[(y_i - \lambda_i)^2 - y_i]$ on $(\sqrt{2\lambda_i})^{-1} g(\lambda_i)$. Two tests are performed concerning the form of heteroscedasticity under the alternative, corresponding to the variance implied by the parametrically richer negative binomial models in the form of the negbin I and negbin-II model. For negbin I we choose $g(\lambda_i) = \lambda_i$ and for negbin II $g(\lambda_i) = \lambda_i^2$ (see Cameron and Trivedi 1986). For patent application at the GPO, we have strong evidence for overdispersion in both versions of the implied variance. The tests indicate weak evidence for overdispersion for patent applications at the EPO only. In the case of patent applications at the USPTO we have

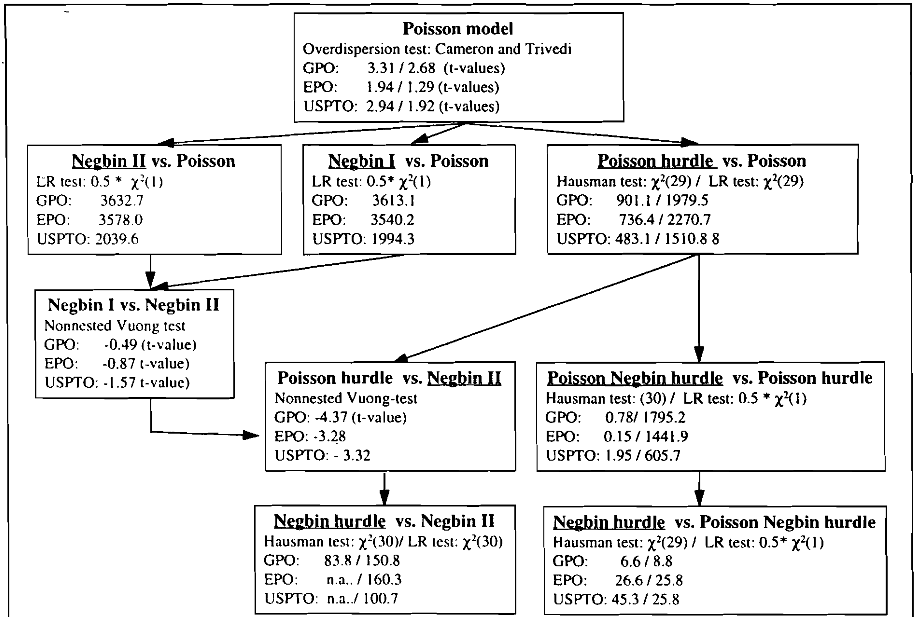
[16] See equation (5) and the adjacent paragraph for the definition of α.

[17] See Cameron and Trivedi (1990, p. 353) or Gourieroux, Monfort and Trognon (1984).

strong evidence only in the first version of the implied variance. Additional robust poisson estimations performed for all three dependent variables show large reductions in the estimated t-values of the estimated coefficients, indicating overdispersion too (see Winkelmann 1994).

These test results let us search for more general models allowing for overdispersion. A first alternative are models assuming a negative binomial distribution for the data generating process. We estimate both models negbin I and negbin II, which imply different forms of heteroscedasticity. Since it is difficult to tell a priori which of the two models is more appropriate for the data set at hand, we test which one performs better. The two versions of the negbin model are not nested. Therefore, we apply the test proposed by Vuong (1989). This test is directional: Large positive t-values favour negbin I model, large negative values of the t-statistic favour the negbin II model, insignificant t-values in the usual sense mean that one cannot discriminate between the two models. As indicated by insignificant t-statistics in all three cases, we cannot reject the null of no difference between the two models negbin I or negbin II.

Figure A1: Testing distributional assumptions for various count data models



Critical values: $\chi^2_{30;0.95}=43.8$; $\chi^2_{30;0.975}=47.0$; $\chi^2_{29;0.95}=42.6$; $\chi^2_{29;0.975}=45.2$; $\chi^2_{1;0.95}=3.8$; $\chi^2_{1;0.975}=5.0$.

Remark: Hausman-type tests are performed using estimated parameters and covariance matrices of both stages of the hurdle model. The table reports Hausman-test for the first stage. Using second stage Hausman-tests we never obtain a positive definite matrice of difference of the covariance matrices. The underlined models mean that there is due to our opinion statistical significance in favour of the underlined model.

We also apply the Vuong-test to decide between poisson hurdle and negbin II model, since these are not nested. Here large positive t-values favour the poisson hurdle model, large negative values of the t-statistic favour the negbin II model. The results show that negbin II is better than poisson hurdle. Since both specification allow for overdispersion this result justifies the assumption that unobserved heterogenity should be accounted for.

As shown by Mullahy (1986) and Winkelmann (1994) the hurdle specification allows for over- and underdispersion at the individual level. This means that every firm in our sample can have it's own variance-covariance relationship.

We use the likelihood ratio to test for $H_0:\theta_1 = \theta_2$, i.e. the equality of the estimated coefficients of the two hurdle stages, to test poisson hurdle against poisson and to test negbin-Hurdle against the negbin II model.[18] In addition, we use Hausman tests, which are of special attractiveness to test the negbin hurdle model against the poisson-negbin hurdle model since it rests on the parameter vector β, not α, and thus circumvents the boundary problem. In two cases it turned out that the Hausman test could not be applied due to the fact that the difference of the covariance-matrices used to compute the statistic failed to be a positive definite matrix.

As obvious from Figure A4 the test strategy implies that a negbin hurdle model is preferable. With respect to the poisson-negbin hurdle model only, the Hausman test and the LR-test do not point in the same direction. Moreover, this conclusion is confirmed by comparing the observed number of firms with a certain number of patents and the predicted number of firms with a given number of patent applications (see Appendix 4). The prediction of count data models are obtained by first calculating for each observation the probability for a certain number of patents and then sum over these individual predicted probabilities for each category (see Winkelmann and Zimmermann 1995). The predicted and observed number of firms within each category (number of patents) are compared in Figure 3, details are reported in the appendix 4. Thus we will report only the results from the negbin hurdle model, noting that the results for the alternative poisson negbin hurdle model do not deviate very much.

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[18] θ is meant to comprise the coefficient vector of the exogenous variables β and the parameter α in case of Negbin hurdle model and to consist of β only in case of Poisson hurdle model.

Appendix 4: A Comparison of Actual and Predicted Counts

Number	Number Observed	Estimated number of firms having a certain number of patents: Negbin Hurdle	Poisson-Negbin H.	Poisson Hurdle	Negbin II	Negbin I	Poisson
German Patent Office							
0	1223	1223.2	1223.8	1223.8	1189.9	1228.4	926.7
1	100	109.6	112	61.1	183.8	98.4	278
2	81	72.3	72.6	60.4	78.1	57.3	134.9
3	63	50.5	50.1	53.1	44.9	40.6	83
4	24	36.8	36.3	44.8	29.8	31.3	56.3
5	48	27.9	27.4	37.1	21.5	25.2	39.8
6	10	21.7	21.2	30.5	16.3	20.9	28.5
7	10	17.2	16.8	24.9	12.9	17.6	20.7
8	13	13.9	13.6	20.3	10.4	15.1	15.2
9	5	11.5	11.2	16.4	8.6	13.1	11.4
10	23	9.6	9.3	13.3	7.3	11.5	8.8
11-15	24	30.3	29.8	37.8	24	40.8	25.2
16-20	16	15.7	15.5	16.1	13.3	24.4	13
21-25	8	9.2	9.2	8.8	8.4	15.7	8.6
European Patent Office							
0	1358	1359	1359.3	1359.3	1189.9	1368.1	1093.6
1	71	85.4	89.6	61.1	183.8	71	240.3
2	71	52.9	53.4	46.6	78.1	40.4	111.3
3	45	35.8	35.3	36.4	44.9	28.3	64.1
4	20	25.6	25	28.6	29.8	21.7	40.9
5	23	19.1	18.5	22.7	21.5	17.4	27.7
6	14	14.7	14.2	18.3	16.3	14.4	19.6
7	4	11.6	11.2	14.9	12.9	12.2	14.3
8	5	9.4	9	12.3	10.4	10.5	10.6
9	3	7.7	7.4	10.2	8.6	9.1	7.9
10	21	6.4	6.2	8.5	7.3	8	6
11-15	24	30.3	29.8	37.8	24	40.8	25.2
16-20	16	15.7	15.5	16.1	13.3	24.4	13
21-25	8	9.2	9.2	8.8	8.4	15.7	8.6
US Patent and Trademark Office							
0	1499	1499.5	1500.4	1500.4	1487.6	1500.2	1325.1
1	40	49.3	51.4	33.4	85.7	44.1	163.5
2	37	32	32.3	29	32	24.5	68.9
3	32	22.1	21.7	23.7	17.5	17	36.7
4	11	15.8	15.3	18.9	11.3	13	22.2
5	20	11.6	11.2	14.7	8	10.4	14.6
6	6	8.8	8.5	11.4	6	8.6	10.2
7	3	6.8	6.5	8.8	4.6	7.3	7.4
8	4	5.4	5.2	6.8	3.7	6.2	5.5
9	1	4.4	4.2	5.3	3.1	5.4	4.2
10	10	3.6	3.4	4.3	2.6	4.8	3.4
11-15	24	30.3	29.8	37.8	24	40.8	25.2
16-20	16	15.7	15.5	16.1	13.3	24.4	13
21-25	8	9.2	9.2	8.8	8.4	15.7	8.6