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Horst Rottmann
Stefan Lachenmaier

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Herausgeber Prof. Dr. Horst Rottmann (FH Amberg-Weiden)
Prof. Dr. Franz Seitz (FH Amberg-Weiden)

Fachhochschule Amberg-Weiden, University of Applied Sciences, Abt. Weiden,
Hetzenrichter Weg 15, D-92637 Weiden
Telefon: +49 961 382-0
Telefax: +49 961 382-110
eMail: Weiden@fh-amberg-weiden.de
Internet: www.fh-amberg-weiden.de

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Employment Effects of Innovation at the Firm Level

Stefan Lachenmaier	**Horst Rottmann**
Ifo Institute for Economic Research at the University of Munich *Poschingerstr. 5* *81679 Munich, Germany* *E-mail: lachenmaier@ifo.de*	*Research Professor at the Ifo Institute for Economic Research at the University of Munich* *University of Applied Sciences Amberg-Weiden* *Hetzenrichter Weg 15* *92637 Weiden, Germany* *E-mail: h.rottmann@fh-amberg-weiden.de*

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Abstract

This paper analyzes empirically the effects of innovation on employment at the firm level using a uniquely long panel dataset of German manufacturing firms. The overall effect of innovations on employment often remains unclear in theoretical contributions due to reverse effects. We distinguish between product and process innovations and additionally introduce different innovation categories. We find clearly positive effects for product and process innovations on employment growth with the effects for process innovations being slightly higher. For product innovations that involved patent applications we can identify an additional positive effect on employment.

Abstrakt

Dieser Aufsatz analysiert die Beschäftigungseffekte von Innovationen auf der Unternehmensebene. Bei der empirischen Analyse wird ein außergewöhnlich langer Paneldatensatz für das Verarbeitende Gewerbe in Deutschland verwendet. Aus theoretischer Sicht ist der Effekt von Innovationen auf die Beschäftigung im Unternehmen auf Grund von gegenläufigen Wirkungen unbestimmt. Wir unterscheiden nicht nur zwischen Produkt- und Prozessinnovationen, sondern berücksichtigen die Bedeutung der Innovationen. Sowohl für Produkt- als auch für Prozessinnovationen finden wir signifikant positive Beschäftigungseffekte, wobei dieser Effekt bei Prozessinnovationen sogar größer ausfällt. Für Produktinnovationen, die mit einer Patentanmeldung einhergehen, finden wir einen zusätzlichen positiven Effekt auf die Beschäftigung.

1. Introduction

This paper delivers empirical evidence for the effects of innovations on employment. It contributes to the existing research by using a uniquely rich dataset of German manufacturing firms. The dataset combines annual surveys over the last 22 years and thus delivers a panel dataset, that allows analyses over a long time horizon. The theoretical literature stresses the importance of the distinction between product and process innovations. But for both types of innovation the overall effects on employment remain unclear, with the effect depending mainly on the demand elasticity of the affected products. Thus, pure theoretical analyses are not able to deliver clear predictions for the effects of innovations on employment, which raises the need for empirical evidence.

With our data set we can analyze the German manufacturing sector for two decades with the possibility to distinguish between product and process innovations. In addition, we introduce different categories of innovation representing different importance levels of the respective innovations. In this paper we concentrate on longer periods and do not try to model the year-to-year employment adjustment processes. We also address the questions of whether the effects differ between small and large firms or differ between firms which are located in former West and East Germany.

The paper is structured as follows. Section 2 gives a short overview about the existing theoretical and empirical literature in this research field. Section 3 presents our identification strategy. Section 4 describes the data base and presents the descriptive statistics. The results are presented in Section 5, Section 6 concludes the paper.

2. The Literature on Innovation and Employment

2.1 Theoretical Literature

In theoretical contributions on the impact of innovation on employment, the direction of the effect of technological progress often remains unclear. An historical overview about the evolution of this field of research is given in Petit (1995).

In the theoretical literature the distinction between product and process innovations has been proven important (Stoneman 1983, Hamermesh 1993, Katsoulacos 1986). For both types of innovation there exist effects on employment that go in opposite directions. We first describe the effects of product innovations. The introduction of new or improved products creates a new demand for these products. This increasing demand leads to an increase in employment in the innovating firm. This is especially true for products that are new to the market. Thus, the expected direct effect of product innovations on employment is positive. However, there also exists an indirect effect. Product innovations can also lead to a (temporary) monopoly of the firm. The firm can take advantage of this situation and increase the product price to maximize its profits. Thus, the employment level might suffer from this reduction in the amount of output, especially if the new products are substitutes for existing products of the firm. So the indirect effect of product innovations on employment is negative. Empirical evidence is necessary to analyze which effects − the expected direct positive effect or the expected indirect negative effect − are stronger and drive the overall effect.

Also for process innovations the overall effect is not clear in theory. As a process innovation usually aims at improving the productivity of inputs, the direct effect of a process innovation can be a reduction in the amount of inputs. This includes labour as a input factor. Considering only this argument, we expect a negative direct effect of process innovations on employment as the same output can be obtained with fewer workers. But, there also exists an indirect effect of process innovations on employment. If the firm passes on the advantage of a cheaper production process to the prices, this might – depending on the demand elasticity – increase the demand for the product. This increase in demand might then lead to an increase in employment.

To sum up the theoretical contributions, a clear statement on the direction of the effect of innovations on employment at the firm level is not possible. The effects can differ significantly depending on the size of the contrary direct and indirect effects, which depend on the prevailing market structure and on the price elasticity of product demand. Thus for both types of innovation empirical evidence is necessary to reveal the directions of this effects.

2.2 Empirical Evidence

The empirical literature on technological progress and its impact on different economic measures is extensive. Researchers have been analyzing this task for a long time, and their analyses differ mainly in the methodology and the data available. What we will concentrate on in this paper is the microeconometric analysis of the effects of innovation on employment.[1] This strand of literature started mainly in the 1990s with the increasing availability of micro data on firms' innovation behavior. An overview of microeconometric

[1] Topics not covered in this paper include the effects on wages and skill-biased technological change.

analyses in this field of research is given in Chennells and Van Reenen (2002). As suggested by theoretical contributions, the empirical analysis usually distinguishes between product and process innovation. In almost all analyses a positive effect of product innovations is found; for process innovations there is also a tendency for a positive effect but the effect is not that clear.

The methods used are widespread as are the countries covered and the variables used. These include the innovation variables (or proxy variables for innovation) as well as control variables. In terms of econometric models one can divide the existing literature mainly in three parts: cross-sectional analyses, analyses of growth rates with data of two different points in time and panel data analyses.

Early contributions are mainly based on cross-sectional data due to limited data availability. Contributions in this line are Zimmermann (1991), Entorf and Pohlmeier (1990) and König et al. (1995). Zimmermann (1991) and Entorf and Pohlmeier (1990) also use data of the Ifo Insitute, but from a different survey, in which the innovation data is not as detailed as in the innovation survey. Zimmermann (1991) concludes that technological progress played an important role in the decrease of employment in 1980. However, the innovation variable he uses refers to a survey question relating explicitly to labor-saving technological progress. Entorf and Pohlmeier (1990), however, show a positive effect of product innovations on employment while process innovations showed no significant effect. König et al. (1995) also use German data, stemming from the “Mannheimer Innovationspanel” in 1993 and also find a positive effect of product innovations on labor demand.

Newer analyses combine two surveys of different points in time and therefore are able to explain the growth rate of employment between these two points in time. Brouwer et al. (1993) are in this line of literature with their analysis of Netherlands data of 1984 and 1989. The authors show a negative effect of total R&D investment on employment growth, but a positive effect for those R&D expenses that are related to creating new products. Blanchflower and Burgess (1998) find a positive relation between process innovations and employment growth in the UK and in Australia. Doms et al. (1995) also show a positive relation between the use of modern technology and employment growth between 1987 and 1991 using firm data of the U.S. manufacturing sector together with data from a technology survey in 1988. Klette und Førre (1998) have matched different data sets for Norway. Census data was combined with several surveys between 1982 and 1989. Their − mainly descriptive − analysis did not show a clear positive relation between innovations (measured as firms conducting R&D vs. firms not conducting R&D) and employment.

With the upcoming availability of the CIS data, more studies about the employment effects of innovations were conducted in different countries. They also mostly fall in the category of papers that analyze employment growth rates as a question in the CIS questionnaire asks explicitly for the employment level at the start and the end year of the 3-year observation period of a CIS survey. Jaumandreu (2003) analyzed Spanish data and found positive effects of a product innovation measure while process innovations had no significant additional effect. Also studies for German CIS data exist. Peters (2004) analyzes employment growth between 1998 and 2000 in a similar way like Jaumandreu using the German CIS3 data. Product innovations show a significantly positive effect on employment growth whereas process innovations showed a negative effect for German manufacturing firms. Using German and Dutch CIS data, Blechinger et al. (1998) find positive effects of product as well as process innovation on employment growth for the Netherlands between 1988 and 1992 and for Germany between 1992 and 1994. A study by Harrison et al. (2005) compares available CIS data across countries. Especially product innovation drives employment growth, which is similar in most countries, but highest in Germany.

The third type − panel studies − are the rarest ones. A first step in this direction is Greenan and Guellec (2000), who use firm panel data, but they match it with a cross-sectional innovation survey. Their results show that innovating firms (and innovative sectors) have created more new jobs than non-innovating firms (less innovative sectors). Their results suggest that, at the firm level, process innovations play the more important role whereas at the sector level product innovations are more important. Panel analyses over a longer time horizon are the contributions of Smolny (1998), van Reenen (1997) and Rottmann and Ruschinski (1998). Smolny (1998) analyzes data of German firms from the Ifo Business Survey and the Ifo Investment Survey from 1980 to 1992. Using pooled OLS regressions, he shows a positive effect of product innovations as well as process innovations.

Van Reenen (1997) matches firm data of firms listed at the London Stock Exchange with the UK innovation database of the SPRU (Science and Technology Policy Research at the University of Sussex). With this data set for 1976-1982 he estimates panel models, which allows him to control for fixed effects, dynamics and endogeneity. But still he finds positive effects of innovation on employment. Rottmann and Ruschinski (1998) carry out analyses with data from the Ifo Institute. The authors find, using a dynamic panel method, positive effects of product innovations, but process innovations showed no significant impact.

All these studies, even the panel studies, are restricted to a relatively limited time horizon. In addition, most of these studies do not include any quality measures of the innovation outputs.

3. The Estimation Strategy

Our identification and estimation strategy combines different elements of the literature mentioned above. We extend the existing literature on innovation and employment not only in terms of a broader variety of innovation variables but also by applying a different estimation strategy.

We assume that labor demand can be described by the following equation in levels,

$$L = f(Z, Q, X) \qquad (1)$$

where L is labor demand, Z is a measure for the technology used in the production process, Q is a measure for the quality of the product and X denotes a vector of additional control variables, which we specify in more detail after Equation (3). Taking log values (denoted by lower case letters) and differencing the equation (denoted by the difference operator Δ) leads to an equation in growth rates. This procedure basically is a first-difference panel approach, which accounts for the possible unobserved firm heterogeneity. Otherwise a spurious relationship between innovation and employment could be generated due to unmeasured factors that are reasonably stable over time like quality or risk tolerance of management. If such effects were present in the level equation, these time-constant firm specific effects drop out by taking first differences:

$$\Delta l = \beta_0 + \beta_1 \Delta z + \beta_2 \Delta q + \beta_3' \Delta x \qquad (2)$$

For the estimation of Equation (2) we need a measure for the progress in the applied technology (Δz) and for the improvement in the product quality (Δq). These changes in the levels can be approximated by our innovation variables. The implementation of a process innovation can be interpreted as the change in the production technology, and the introduction of a product innovation can be interpreted as a change in the product quality.

In the empirical implementation we therefore use $\Delta z = I^{Pc}$ for the yearly progress in technology and analogous $\Delta q = I^{Pd}$, where the dummy variables I^{Pc} and I^{Pd} denote the introduction of process innovations and product innovations.

Since the unobserved firm effects are already differenced out, we can – following the first difference panel approach – estimate this differenced equation by least squares regressions. Equation (3) is a static version of a labor demand equation. Adjustment costs for employment and expectation formation will induce dynamics to Equation (3). Modeling these adjustment processes is a complex topic (Hamermesh and Pfann 1996), especially within small firms.[2] Furthermore, innovations do not only have employment effects in the year of their introduction; they are likely to influence employment growth in the following years, too. Little is known about the delayed effects of innovation. Therefore, we use an estimation strategy employed in labor market analyses, where one does not expect instant (yearly) effects of different institutional arrangements on unemployment (e.g. Nickell 1997, 2003 and Blanchard and Wolfers 2000). In this kind of analyses averages for longer time periods are calculated, usually for 5-year-periods, to smooth out the year-on-year noise and detect long-term effects of institutions on the labor market. Putting our main focus in this study on effects over a longer horizon, we apply this estimation technique and calculate average yearly growth rates over four and five year periods. In the following we suppress the subscript *i* for the firm.

$$\left(\Delta l_{t+\tau,t} / \tau\right) = \beta_0 + \beta_1\left(\Delta z_{t+\tau,t} / \tau\right) + \beta_2\left(\Delta q_{t+\tau,t} / \tau\right) + \beta_3'\left(\Delta x_{t+\tau,t} / \tau\right) + \left(\Delta u_{t+\tau,t} / \tau\right) \qquad (3)$$

with $\mathrm{t} = 1982 + j(\tau + 1)$, $j = 0,1,2,\ldots$

The values of the variables are the calculated yearly average growth rates per period. So $\Delta l_{t+\tau,t} / \tau = (l_{t+\tau} - l_t) / \tau$ stands for the average yearly employment growth rate per firm within one period. For example, with $\tau = 4$, we have the periods 1982 - 1986, 1987 – 1991 and so on. Due to our sample of 22 years, we calculate averages for three 4-year periods and two 5-year periods. These are the periods from 1982-1986, 1987-1990, 1991-1995, 1996-1999 and 2000-2003.[3] By setting a border between 1990 and 1991 we also account for the problem that arises in data due to German reunification. All data up to 1990 refer to

[2] In smaller firms the adjustment is more complex because of the indivisibility of persons and the usually higher relation of fixed to variable adjustment costs in smaller firms.

[3] We also tested several other lengths of periods; details are described in chapter 5.2.

former West Germany; all data since 1991 refer to Germany. We use these periods as time units in our panel estimations. u_t is an i.i.d. idiosyncratic error term.[4] As outlined after Equation (2) we approximate the average yearly growth rates $(z_{t+\tau} - z_t)/\tau$ and $(q_{t+\tau} - q_t)/\tau$ with the average number of years per period in which a firm gave a positive answer to the questions whether any process or product innovation was introduced. The variables in x include the average yearly growth rates per period of the real hourly wage rate and the real Gross Value Added in the sector. Since the wage rates of the individual firms are not observed, the average sectoral real hourly wage rate is used here as the best proxy available. Real Gross Value Added is included as a control variable for the overall demand situation in the respective sector.

Additionally we introduce the variable l_{it} as a regressor, which denotes the log of the employment start level of a firm in the respective period. l_{it} controls for the possible differences of the growth rate in small and large firms. Or, in other words, it is a test for Gibrat's Law, which states that the growth rate of a firm is independent of the size of a firm (Gibrat 1931). Many studies have dealt with the empirical test of Gibrats's Law, especially in manufacturing firms. The underlying result of these studies is that Gibrat's Law does often not hold in the manufacturing sector, especially for small firms (e.g. Sutton 1997, for Germany: Wagner 1992, Harhoff et al. 1998). There is a strong tendency that initially smaller firms tend to grow at a faster rate than initially large firms. Only for special samples, large manufacturing firms (Hall 1987, Evans 1987) or for service firms (Audretsch et al. 2004) there are empirical results that lead to the assumption that Gibrat's Law is valid in these cases.

Our estimation strategy might raise some concern about estimating causal effects. The reason for that is the problem of endogeneity of the innovation variables. They might be correlated with the error term of the labor demand function. But, following this argument, one has to keep in mind that the unobserved individual effects cannot be responsible for such a correlation since they dropped out as we use growth rates in our estimation equation. The only factor leading to an endogeneity problem might be a correlation of the innovation variables with the idiosyncratic error term, resulting from shocks affecting employment and innovation. In case of such a shock, a possible solution of this problem in our estimation strategy would be an instrumental variable strategy.

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[4] If the idiosyncratic errors u_t are i.i.d. the $(u_{t+\tau} - u_t)/\tau$ for the different periods are not correlated, because the periods have no years in common.

The questionnaire contains two questions that might offer useful instruments. First, firms are asked which innovation impulses led the firm to start the innovation process and second, which factors hampered them. But most of these possible instruments can be excluded as not being exogenous to the error term. Only few variables, like external innovation impulses coming from technical literature or from patent specifications can be considered at all. As for factors hampering innovation, the choice is even more limited as all hampering factors that are available over the complete period relate to firm internal obstacles.

In addition, the construction of these instruments leads to further problems. Beside the question of whether these instruments are uncorrelated with the error term, the construction of the survey questionnaire raises some concerns: This information is not available for all firms. Firms that indicated at the beginning of the questionnaire that no innovations were necessary do not answer these questions about innovation impulses and innovation obstacles. Therefore we have to make strong assumptions for those firms: Either we leave the instruments as missing for firms that responded that no innovation was necessary or we replace the missing information in innovation impulses and hampering factors by the value zero as a best approximation. This would be the strategy that is implicitly assumed in the questionnaire when respondents are led to jump over the detailed question when they considered innovation as not necessary. This strategy, however, raises again the problem of endogeneity. If innovation itself is considered to be endogenous, instruments that are set to zero if innovation was not necessary are also likely to be endogenous.

Nevertheless, we tested both strategies. Replacing missing values by zero led − as expected − to a rejection in the Sargan test of the null hypothesis that the instruments are exogenous. Leaving the instruments as missing reduces the estimation sample dramatically. In these specifications the Sargan of overidentifying restrictions does not reject the null hypotheses and innovation itself is to be treated as exogenous according to Durbin-Wu-Hausman test.[5]

[5] Results are available from the authors on request. For example we use innovation impulses stemming from “technical literature” or “patent specifications” and the hampering factor of a “too low readiness of managers to support innovative activity” as instruments. This delivers a Sargan test of 10%, but the Durbin-Wu-Hausman test does not reject the null of the exogeneity of innovation with a p-value of 29%.

4. Database and Descriptive Statistics

4.1 The Ifo Innovation Survey

The data source used in this analysis is the Ifo Innovation Survey. The Ifo Innovation Survey is conducted yearly by the Ifo Institute for Economic Research at the University of Munich. It was started in 1982. Since that time the Ifo Institute has collected the answers of, on average, 1500 respondents each year, including East German firms since 1991. The latest data used in this analysis, stem from the questionnaire in 2004, which describes the innovation behavior of the year 2003. This survey gives us a total sample of 33,146 observations from 7,014 different firms over 22 years from 1982 to 2003.

The questionnaire offers different innovation measures. The first one is the simple information of whether the firm has introduced any innovation during the last year. This information is available for product as well as for process innovations, a distinction proposed by theoretical models (see Section 2.1). One can argue that a potential drawback of the simple innovation variable is the lack of detailed information about the importance of the innovation. But, as the discussion for a “correct” measurement of innovation is still ongoing in the literature, we of course do not claim to have a perfect measure for innovation here. Other innovation variables like R&D or patents also have advantages and disadvantages. A comparison of the Ifo innovation measure with other popular measures is given in Lachenmaier and Wößmann (2006).

While the simple questions on having introduced innovations is a good starting point, it does not distinguish between different levels of importance of the innovations. Therefore we use additional questions of the Ifo Innovation Survey to introduce different levels in the importance of an innovation.[6] The first information we use is the question if any R&D was necessary for the implementation of the innovation. This sorts out innovations that stem only from spontaneous ideas and which reflect − with a greater probability − minor adjustments in existing products or production processes. Another information we use is whether any patent applications were filed during the innovation process. This should only be true for important and market relevant innovations because patent applications are expensive and are only filed if the expected revenues are larger than these costs. So we can use three different categories of innovations in our estimations, that reflect the importance of the innovations.

[6] Many of the CIS related studies use the “share of sales related to new products” or the distinction between “products new to the market” and “products new to the firm” as indicators for the importance of product innovations (see e.g. Jaumandreu 2003 or Peters 2004).

4.2 Descriptive Statistics

The Ifo Innovation Survey consists of an unbalanced panel with 33,146 observations, collected from 7,014 firms over the 22 years from 1982 to 2003. The survey is conducted among German manufacturing firms.[7] But as described in our estimation strategy in Section 3, we do not use yearly data but the averages over four- or five-year periods. Therefore we will present descriptive statistics according to the observation units in our regressions, which are the average values per period. If a firm has not answered in all years during a period, we calculate the averages of the available observations as the best estimation for the whole period. Due to the estimation strategy we need for each firm at least two observations within one period to be able to calculate a growth rate. This leads to an unbalanced panel data set of 9,142 observations, which stem from 4,567 different firms. Note that the time index now refers to periods and no longer to single years. Detailed comparisons of the estimation sample and the original sample can be found in Tables A1 to A3 in the Appendix. The distribution of firms across industries and size classes remains very stable (Table A1). As descriptive statistics of the variables show (Tables A2), there are only small differences between the estimation sample and the original sample. Table A3 gives detailed information about how often firms enter the estimation sample if we consider periods as time index.

Table 1 shows the descriptive statistics of the estimation sample. The mean of the dependent variable – the average yearly employment growth rate per period – shows a negative sign. That means that the employment level in the average firm of our sample is slightly declining within a period.[8] This growth rate is measured as the difference in log values divided by the respective length of the period ($(\log L_{t+\tau} - \log L_t)/\tau$).[9] Unfortunately, the dataset only allows to use employee headcounts as a measure for employment as the survey does not distinguish between part-time and full-time workers. The innovation variable is the average of how often a firm responded during a four or five year period with "yes" to the yearly question of whether an innovation was introduced. Thus, a firm that has innovated in all years has an innovation value of one, a

[7] The distribution of firms across industries and size classes can be found in Table A1 in the Appendix.

[8] This does not necessarily imply that the overall employment level in an industry or in the whole economy is declining. Since we only observe manufacturing firms, these numbers might reflect a tendency towards a structural shift from manufacturing to service sectors. Another explanation might be a tendency to an increase in outsourcing.

[9] $\log L_{t+\tau}$ denotes the log of the employment level in the last year observed during a period, $\log L_t$ denotes the log of the level of employment in the first year observed during a period and τ denotes the time between the first and the last year observed during a period.

firm that has not introduced any innovations during a period has an innovation value of zero and a firm that has reported an innovation in half of the years has an innovation value of 0.5.

Table 1: Descriptive Statistics

	Obs	Mean	Std. Dev.	Min	Max
Employment growth (Δlog)	9142	-0.016	0.261	-2.708	2.996
Innovation	9142	0.497	0.412	0	1
Product innovation	9142	0.406	0.410	0	1
Process innovation	9142	0.317	0.365	0	1
Product innovation (R&D)	9136	0.332	0.392	0	1
Process innovation (R&D)	9100	0.196	0.312	0	1
Product innovation (Patents)	9136	0.192	0.330	0	1
Process innovation (Patents)	9100	0.023	0.119	0	1
Employment start level (log)	9142	4.682	1.506	0	11.513
Sectoral GVA growth	9142	0.005	0.046	-0.265	0.283
Sectoral real wage growth	9142	0.018	0.026	-0.231	0.428

N=4567, n=9142, Avg.T=2.002

Notes: *N* denotes the number of different firms in the sample, *n* denotes the numbers of total observations, *Avg. T* denotes the average number of periods that a firm is in our estimation sample.

The sample mean of this variable is 0.497. But it is also important to know that in 2,964 cases (out of the 9,142 observations) firms have not innovated at all during a period (i.e. their average for the period equals zero) and in 2,903 cases, the innovation value is one, i.e. the firm has innovated in all observations during a period. This gives us 5,867 of 9,142 cases (equals 64%) where no change in the innovation variable is observed within one period. With our dataset we are able to split this variable into product and process innovations – which are not mutually exclusive, i.e. a firm can either tick no innovation, one of the innovation types or both types. The dataset shows that product innovations were implemented more often than process innovations.

We can further look at the innovations for which R&D was necessary or patent applications were filed. Product innovations with R&D were introduced by 33.2%, process innovations with R&D by 19.6%. For innovations for which patent applications were filed we find a very different share for product and process innovators. While product innovations with patent applications were indicated in 19.2%, process innovations with patent applications are very rare and are only indicated in 2.3% of our estimation sample. This very low number should be considered in the following regressions.

The employment start level, which is the number of employees in the first year of a period is, expressed in log values, on average 4.682. The next two variables of Table 1 are calculated as the average yearly growth rates within the corresponding period. The growth rate of the Gross Value Added on the industry level accounts for economic development of the corresponding industry. The mean value is slightly positive. Also as a control variable we include the sectoral real wage rate growth, which is on average also positive in our sample.

5. Results

In this section we present the results of several specifications of estimating Equation (3). In Section 5.1 we only distinguish between product and process innovations, in Section 5.2 we introduce different categories for both types of innovation. In Section 5.3 we present results for different firm sizes and different regional locations of the firm.

5.1 Product and Process Innovations

Table 2 presents the regressions in which the innovation is split into product and process innovations, which are not mutually exclusive (see Section 4.2). The innovation variables are, as described in Section 3, the average per period of how many times the firms responded with "yes" to the yearly questions of whether any product (or process) innovations were introduced. So the regression coefficient has to be interpreted as the difference between a firm that has innovated each year during the period and a firm that had no innovation during the period.

Table 2: Product and Process Innovations

Dependent Variable: Average Yearly Employment Growth

		(1)	(2)	(3)
	Estimated Coefficients	OLS standard errors	Heteroskedastictiy robust standard errors	Covariance robust standard errors
Employment start level	-0.034	(0.002)***	(0.003)***	(0.003)***
Real wage growth	-0.437	(0.132)***	(0.162)***	(0.161)***
Real GVA growth	0.257	(0.081)***	(0.102)**	(0.102)**
Product innovation	0.033	(0.008)***	(0.009)***	(0.009)***
Process innovation	0.057	(0.009)***	(0.009)***	(0.009)***
Year intervals	incl.			
Sector	incl.			
States	incl.			
Constant	0.112	(0.026)***	(0.024)***	(0.026)***
Observations	9142			
Adj. R-squared	0.039			

Regression coefficients are * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 shows different specifications in terms of heteroskedasticity and of correlation between error terms, but as can be easily seen the difference in the standard errors is very small. Regression (1) shows standard OLS standard errors, Regression (2) corrects for possible heteroskedasticity and Regression (3) additionally relaxes the assumption of independency within the observations of the same firm in different time periods. The very small change in the size of the standard errors can be taken as a sign for a robust specification. In the following we will only present results which allow for heteroskedasticity and dependence of the idiosyncratic error terms within firms, as in Regression (3).

The control variables show the expected signs. The employment start level shows a negative sign and is significantly different from zero at the 1% level. This gives strong evidence for the hypothesis that large firms grow more slowly than smaller firms and thus contradicts Gibrat’s Law. This finding is in line with other work analyzing Gibrat´s Law in manufacturing industries (see Chapter 3). The sectoral Gross Value Added growth rate shows a positive sign and is significant at the 5% level. This is no surprise as this result shows that firms benefit from the sectoral development. The wage growth has a negative effect on employment. The coefficient can be interpreted as the wage elasticity. A one percent higher real hourly wage rate in the sector leads to a 0.4% smaller yearly employment growth rate in the firm. In all specifications dummy variables are included for the German states (“Bundeslaender”), for the industry sector on a NACE 2digit level and for the year intervals.[10]

The variables of main interest, however, are the innovation variables. In these specifications we start with the simple innovation indicator variables. Both product and process innovations show a significantly positive effect on employment growth. Recall that in our estimation strategy, the innovation coefficient takes on the value zero if the firm has never innovated during a certain period and takes on the value one if it has innovated in each year of the period. Thus the size of the coefficient is to be interpreted as the difference between a firm that has never innovated within a period and a firm that has innovated in each year of a period. We can see that for product innovations this difference accounts for a 3.3% higher employment growth per year, for process innovations it is even higher at

[10] Table A1 in the Annex replicates the results of Specification (3) in Table 2, but also shows the effects for the dummy variables. The coefficients for the dummy control variables are only presented once since they remain almost unchanged in the following specifications. Statistical tests report joint significance at the 10% level for the year dummies, at the 5% level for the states dummies and at the 1% level for the NACE dummies.

5.7%, where both effects are significant at the 1% level. This result supports the hypothesis that the indirect effect of process innovations are present and firms pass on the productivity gains to lower prices and thus can also increase demand and employment. This result of a positive effect of process innovations on employment is not very present in other studies, but is in line with the results of Greenan and Guellec (2000): They also find that process innovations lead to higher employment growth than product innovations at the firm level.

5.2 Categories of Innovation

In this section we will further exploit the detailed questions about the innovation behavior of the Ifo Innovation Survey questionnaire and introduce different innovation categories as described in Chapter 4. On top of the simple product and process innovation variables we add variables that can be interpreted as a level of importance of the innovations introduced. For both product and process innovations, we also get the information if there were R&D activities necessary for the implementation of the innovation and if during the innovation process any patent applications were filed. These variables are to be interpreted as interaction variables since they can only take on a positive value if a product (or process) innovation was implemented. We present the results for these innovation variables in Table 3. In Specification (4) we only distinguish between innovations, innovation with R&D and innovations with patent applications, i.e. we do not consider a distinction between product and process innovation. In Specification (5) we distinguish between both the importance and the type of innovation.

Table 3: Different Innovation Categories

Dependent Variable: Average Yearly Employment Growth

	(4)		(5)	
Employment start level	-0.034***	(0.003)	-0.035***	(0.003)
Real Wage growth	-0.439***	(0.161)	-0.444***	(0.162)
Real GVA growth	0.260**	(0.102)	0.256**	(0.102)
Innovation	0.063***	(0.014)	---	
Innovation (R&D)	-0.007	(0.014)	---	
Innovation (patents)	0.026**	(0.011)	---	
Product innovation	---		0.044***	(0.017)
Process innovation	---		0.050***	(0.013)
Product innovation (R&D)	---		-0.027*	(0.016)
Process innovation (R&D)	---		0.006	(0.014)
Product innovation (patents)	---		0.026**	(0.012)
Process innovation (patents)	---		0.031	(0.025)
Year intervals	incl.		incl.	
Sector	incl.		incl.	
States	incl.		incl.	
Constant	0.107***	(0.026)	0.119***	(0.026)
Observations	9140		9096	
Adj. R-squared	0.038		0.039	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

As for the control variables they all show nearly exactly the same values as in the corresponding specifications above. Our main interest in these results lies in the different innovation variables. In Specification (4) we use the different categories of innovations. It confirms that the simple innovation variables are significant, and in addition we find that the question of whether R&D was necessary does not lend any support for the theory that these innovation have a higher effect on employment growth. But the innovations that were accompanied by a patent application show an additional significantly positive effect on the employment growth.

In Specification (5) we split the innovation categories additionally into product and process innovations. Simple product and process innovations again show a significantly positive effect. R&D as in the specification before does not play a highly significant role. The negative coefficient for product innovations is surprising but not statistically significant at the 5% level. Product innovations accompanied by patent applications show a significantly additional positive effect, which is not the case for process innovations. But if we look at the numbers of how many firms have implemented process innovations accompanied by patent applications, this might explain the high standard error, which is responsible for the insignificance of the effect. Only 2.3% of our sample introduced process innovations with patent applications whereas 19% introduced product innovations with patent applications.

5.3 Robustness and Heterogeneity of the Effects

First we test the stability of our results with respect to the chosen lengths of the time periods – from 3-year periods to 9-year periods. In the first case there are three periods before reunification, beginning with the year 1982, and four periods after the reunification, ending with the year 2002. In the second case there is one period before (1982–1990) and one after (1991–1999) reunification. The effects show very similar behavior as in our preferred model described above. In the following, we therefore stick to the models with four- and five-year periods.[11]

Second, we want to analyze if results differ between several subsamples. Therefore we spilt the sample according to firm size (Table 4) and firm location (Table 5). We start with looking at the different effects across firm size classes. We present the results for firms with an employment start level (at the begin of a period) smaller than 200 employees and for firms with equal to or more than 200 employees.[12]

Table 4: Different Firm Sizes

Dependent Variable: Average Yearly Employment Growth

	(6) Fewer than 200 employees		(7) Equal or more than 200 employees	
Employment start level	-0.044***	(0.005)	-0.025***	(0.006)
Real wage growth	-0.498**	(0.215)	-0.399	(0.250)
Real GVA growth	0.157	(0.145)	0.405***	(0.140)
Product innovation	0.044***	(0.012)	0.018	(0.013)
Process innovation	0.064***	(0.012)	0.044***	(0.013)
Year intervals	incl.		incl.	
Sector	incl.		incl.	
States	incl.		incl.	
Constant	0.142***	(0.030)	0.067	(0.060)
Observations	6062		3080	
Adj. R-squared	0.035		0.031	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Specification (6) shows that for smaller firms the employment start level and the wage growth remain significant, but the sectoral GVA growth rate does not show a significant

[11] Estimations results for other period lengths can be obtained from the authors.

[12] Results are very similar if we set the cut-off point at 500 employees.

effect any more. For larger firms (Specification (7)), the employment start level is also still significant, but the wage growth and GVA growth show different effects than for smaller firms. The sectoral real wage growth is no longer significant, though the point estimate remains almost the same, but the standard error increased. The sectoral GVA growth shows strong significance for larger firms. This result – together with the insignificant coefficient of Specification (6) – is not too surprising since the large firms are the ones that are mainly responsible for the sectoral figures.

The negative sign of the employment start level is again in line with earlier findings in the literature, that Gibrat's Law does not hold in the manufacturing sector. The absolute value of the coefficient is smaller for large firms, i.e. there is a tendency that Gibrat's Law is more relevant in the sub-sample of large firms. This is in line with other empirical work on Gibrat's Law (e.g. Sutton 1997, for Germany: Wagner 1992, Harhoff et al. 1998).

But also the innovation variables show different effects. For small firms we find significantly positive effects for both types of innovation, with the coefficients being a bit higher than in our baseline Specification (3). For large firms it is interesting to see that product innovations do not affect the employment growth significantly. Only process innovations show a significantly positive effect. Standard errors do not increase stringly, so the insignificance is not due to a lack of statistical power. So a conclusion here would be that both product and process innovations are important only for small firms to grow; in large firms it seems to be more important to improve the production technology by implementing new process innovations.

The second test for heterogeneous effects accounts for a split of the sample between West and East German firms. Therefore, we only take the data from 1991 to today. For this newer time period we have both former West German firms and former East German firms in our sample and are able to distinguish between these two groups. In Table 5 we distinguish in the location of the firm.

Table 5: Different Regions

Dependent Variable: Average Yearly Employment Growth

	(8) 1991-2003		(9) West 1991-2003		(10) East 1991-2003	
Employment start level	-0.039***	(0.004)	-0.034***	(0.004)	-0.060***	(0.008)
Real Wage growth	-0.500**	(0.220)	-0.572**	(0.255)	-0.471	(0.433)
Real GVA growth	0.282**	(0.124)	0.341**	(0.137)	0.134	(0.244)
Product innovation	0.053***	(0.012)	0.049***	(0.014)	0.066***	(0.024)
Process innovation	0.052***	(0.013)	0.062***	(0.014)	0.036	(0.028)
Year intervals	incl.		incl.		incl.	
Sector	incl.		incl.		incl.	
States	incl.		incl.		incl.	
Constant	0.099**	(0.039)	0.076*	(0.039)	0.200***	(0.048)
Observations	5485		4136		1349	
Adj. R-squared	0.038		0.031		0.087	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Specification (8) presents results for the years between 1991 and 2003 for whole Germany. Comparing these results with Table 2 (1982-2003) one can find only minor differences in the estimation results. After 1991 the product innovations show significant positive effect of about the same size as process innovations.

For firms located in the West Germany (Specification (9)) we find very similar effects to the overall estimates. But the effect on yearly employment growth of the sectoral GVA growth in former East Germany (Specification (10)) is only about one third of the effect in West Germany. Also for firms in former East Germany only product innovations show a significant effect. It seems more important to introduce new products than to improve the production technology. However, this result is less clear. On the one hand, the coefficient of the process innovation variable decreases but on the other hand its standard error increases strongly in Specification (10).

6. Conclusions

This paper contributes to the literature on the employment effects of innovation. Our empirical analyses were based on a uniquely long time period of innovation data and, in addition, we introduced different categories of innovation which can be interpreted as different importance levels of the innovations. Our analysis gives strong evidence that innovations have a significantly positive effect on employment growth in German manufacturing firms. This is true for both types of innovations: for the introduction of product innovations as well as for the implementation of process innovations. Process innovations showed a higher effect on the employment growth rate than product innovations in most cases.

Looking at different innovation categories, it does not seem to have a significant additional effect if the innovations are based on R&D efforts. But one can identify an additional positive effect for product innovations that involved patent applications. These innovations seem to be of a higher importance for employment growth than the broader defined innovations.

We also tested for heterogeneous effects. First, we tested the effects of innovation on employment for different firm sizes. As it turned out, only process innovations have a significant effect in large firms, whereas in small firms both types of innovation are significantly positive. A split between West and East German firms is not without problems, as our East German sample is relatively small and standard errors increase in this regression. However, product innovations are still strongly significant in East Germany, while the coefficient for process innovations decreases. In West Germany results are very similar to overall results and do not differ very much between the periods before and after the reunification.

Further research will delve into the dynamics of the adjustment processes by using the yearly data of the innovation survey and dynamic panel analysis methods.

Appendix

A. Data Set

We use the Ifo Innovation Survey for our study. This survey is conducted yearly by the Ifo Institute for Economic Research in Munich, Germany. It covers all manufacturing sectors, all firm size classes and collects information from about 1500 respondents per year.[13] For our analyses we use the survey from 1982 to 2004. The distribution of responding firms is given in Table A1. The numbers before the slash denote the number of firms in our estimation sample. The numbers after the slash denote the distribution in the original Ifo Innovation Survey sample. Remember that we lose observations due to our estimation strategy described in Chapter 3. But, as we can see from Table A1 the distribution hardly changes. Table A1 compares the size of the firms in their first year of appearance in the sample.

[13] An overview on previous work with the Ifo Innovation Survey and additional information on the availability of data sets of the Ifo Institute can be found in Abberger et al. (2007).

Table A1: Number of Different Firms

		-49 employees	50-199 employees	200-499 employees	500-999 employees	1000+ employees	Total
15	M.o. food products and beverages	176/262	120/160	27/40	18/23	9/11	350/496
16	M.o. tobacco products	5/6	3/4	1/4	0/0	3/3	12/17
17	M.o. textiles	42/79	90/155	50/85	8/21	9/8	199/348
18	M.o. wearing apparel	48/85	46/84	21/28	779	5/5	127/211
19	Leather	28/44	36/61	17/21	1/0	1/3	83/129
20	M.o. wood and wood products	150/227	64/97	12/13	0/4	1/1	227/342
21	M.o. pulp, paper	61/101	88/125	42/52	19/21	8/12	218/311
22	Publishing, printing	125/202	128/173	40/54	12/15	5/9	310/453
23	M.o. coke, fuel	0/1	4/3	1/2	1/6	5/7	11/19
24	M.o. chemicals	50/127	33/77	15/36	3/11	9/14	110/265
25	M.o. rubber, plastic products	142/246	143/206	37/50	18/23	12/15	352/540
26	M.o. no-metallic mineral products	122/185	105/167	56/69	21/31	14/17	318/469
27	M.o. basic metals	13/24	25/40	16/20	11/16	11/14	76/114
28	M.o. fabricated metal products	153/244	161/230	82/117	21/32	14/23	431/646
29	M.o. machinery and equipment	151/256	265/454	177/260	85/127	83/113	761/1210
30	M.o. office machinery and computers	3/4	2/5	1/5	0/0	4/6	10/25
31	M.o. electrical machinery	59/103	95/135	65/92	37/46	25/28	281/404
32	M.o. radio, TV	11/19	32/40	26/40	17/20	20/29	106/153
33	M.o. medical and optical instruments	75/117	69/103	32/36	15/30	15/18	206/304
34	M.o. motor vehicles	12/19	20/40	19/19	7/10	28/37	86/125
35	M.o. other transport equipment	2/5	6/11	8/8	0/1	13/15	29/40
36	M.o. furniture, manufacturing n.e.c.	89/136	116/181	42/59	14/59	3/5	264/398
	Total	1517/2497	1651/2551	787/1110	315/463	297/393	4567/7014

Notes: Numbers before/after slash denote number of different firms in the estimation sample/original sample.

Table A2 compares descriptive statistics for the estimation sample and the original sample. The descriptive statistics also do not reveal any large differences between the estimation sample and the original sample. The employment variable is slightly higher in the original sample. However, this variable is not completely comparable. For the estimation sample, this number refers to the average of the firm size in the first year of observation with a period. For the original sample we simply use the total average of all observations in the sample. The innovation variables do even show less differences. The mean values of the innovation and also of the two types of innovation remain almost unchanged.

Table A2: Descriptive Statistics in Estimation and Original Sample

	Estimation sample			Original Sample		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Employment Start Level	9142	444.751	2720.260	33146	453.391	2968.328
Innovation	9142	0.497	0.412	32672	0.493	0.500
Product Innovation	9142	0.406	0.411	32672	0.402	0.490
Process Innovation	9142	0.317	0.365	32672	0.314	0.464

Table A3 shows how often the firms responded in our estimation sample. Remember that the time index does not refer to single years but rather to time periods as described in Chapter 3. Also remember, that we need at least two observations of a firm within one time period to be able to calculate yearly average growth rates within one period. As we can see in Table A3, 254 firms answered at least twice in all five time periods. For 353 firms we have the necessary information for four time periods. This goes on to 2,178 firms which we observe only for one period.

Table A3: Distribution of Firms in the Estimation Sample

T	N	n
5	254	1270
4	353	1412
3	718	2154
2	1064	2128
1	2178	2178

T: Number of periods in estimation sample per firm
N: Number of different firms which answered in T periods
n: Number of observations (n=N*T)

B. Additional Table

Dependent Variable: Average Yearly Employment Growth

	(3a)	
Employment start level	-0.034***	(0.003)
Real Wage growth	-0.437***	(0.162)
Real GVA growth	0.257**	(0.102)
Product innovation	0.033***	(0.009)
Process innovation	0.057***	(0.009)
Year 1987-1990	-0.001	(0.008)
Year 1991-1995	-0.022**	(0.009)
Year 1996-1999	-0.015	(0.010)
Year 2000-2003	-0.008	(0.011)
Man. of tobacco products (16)	0.003	(0.035)
Man. of textiles (17)	-0.039**	(0.017)
Man. of wearing apparel (18)	-0.015	(0.025)
Tanning and dressing of leather (19)	-0.037	(0.027)
Man. of wood and wood products (20)	-0.034**	(0.016)
Man. of pulp, paper and paper products (21)	0.008	(0.014)
Publishing and printing (22)	-0.002	(0.012)
Man. of coke, and petroleum products (23)	0.001	(0.075)
Man. of chemicals (24)	-0.020	(0.020)
Man. of rubber and plastic products (25)	-0.027**	(0.013)
Man. of other non-metallic mineral products (26)	-0.002	(0.015)
Man. of basic metals (27)	0.043*	(0.025)
Man. of fabricated metal products (28)	-0.006	(0.013)
Man. of machinery and equipment n.e.c. (29)	-0.007	(0.012)
Man. of office machinery and computers (30)	0.026	(0.131)
Man. of electrical machinery and apparatus (31)	-0.003	(0.017)
Man. of radio, television, communication (32)	0.049*	(0.027)
Man. of medical and optical instruments (33)	-0.036**	(0.016)
Man. of motor vehicles (34)	0.056***	(0.020)
Man. of other transport equipment (35)	0.026	(0.029)
Man. of furniture; manufacturing n.e.c. (36)	-0.016	(0.013)
Hamburg	0.004	(0.030)
Schleswig-Holstein	0.033	(0.032)
Bremen	0.026	(0.033)
Lower Saxony	0.030	(0.024)
North Rhine Westphalia	0.023	(0.022)
Rhineland Palatinate	0.040	(0.026)
Hesse	0.035	(0.023)
Baden Wurttemberg	0.037	(0.022)
Bavaria	0.023	(0.022)
Saarland	0.027	(0.051)
Mecklenburg-West Pomerania	0.013	(0.040)
Brandenburg	0.028	(0.034)
Saxony Anhalt	-0.011	(0.028)
Saxony	-0.027	(0.026)
Thuringia	0.055**	(0.028)
Constant	0.112***	(0.024)
Observations	9142	
Adj. R-squared	0.039	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Residual categories: Year 1982-1986, Berlin

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