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Employment Effects of Innovation at the Firm Level

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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 introduce in addition 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. The effects are stronger in small firms and differ between firms in former West and East Germany.

JEL Codes: J23, O30, L60
Keywords: innovation, labour demand, employment, firm size, panel data

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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 annually 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 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. 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. In this paper we concentrate on longer periods and do not try to model the year-to-year employment adjustment processes. This becomes especially difficult for small firms, which are also part of our dataset.[1]

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 Theory

In theoretical contributions on the impact of innovation on employment, the direction of the effect of technological progress often remains unclear. Researchers have been analyzing this task for a long time, and their analyses differ mainly in the methodology and the data available. An historical overview about the evolution of this field of research is given in Petit (1995).

[1] See e. g. Hamermesh / Pfann (1996)

In the theoretical literature the distinction between product and process innovations has been proved important (Stoneman 1984, Hamermesh 1993, Katsoulacos 1986). Whereas for product innovations it is meanwhile generally assumed that they enhance employment via a higher demand created by the introduction of new products or an improved quality of existing products, it is especially the effects of process innovations that leave open questions.

But for both types of innovation there are effects on employment that go in opposite directions. 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. But the innovation can also lead to a (temporary) monopoly of the firm or at least to a very high market share of the firm. If the firm takes advantage of this situation and increases the product price to maximize its profits the employment level may suffer from this reduction in the amount of output. Also for process innovations the overall effect is not clear in theory. As a process innovation improves the labour productivity, the direct effect of a process innovation might reduce the number of workers since the same output can be achieved by fewer workers. But, if this advantage of a cheaper production process is passed on to the prices, this might increase the demand for the product. This increase in demand might then — depending on the demand elasticity — lead to an increase in employment.

To sum up the theoretical contributions, a clear statement is not possible on the direction of the effect of innovations on employment at the firm level. 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.

2.2 Empirical evidence

The empirical literature on technological progress and its impact on different economic measures is extensive. What we will concentrate on in this paper is the microeconometric analysis of the effects of innovation on employment.[2] This strand of literature started mainly in the 1990s with the increasing availability of micro data on firms' innovation behaviour. An excellent overview of microeconometric analyses in

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

this field of research is given in Chennells / Van Reenen (1999). 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 analyses are not that clear.

The methods used are widespread as are the countries covered and the employed variables. 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 the growth rates with data of two different points in time and panel data analysis.

Early contributions are mainly based on cross-sectional data due to the 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. 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 found a positive effect of product innovations on labour 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 related to creating new products. Blanchflower and Burgess (1998) find a positive relation between process innovations and employment growth in the UK in 1990 and in Australia in 1989/1990. 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 Forre (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. Using German data from the Community Innovation Survey (CIS3), Peters (2004) analyzes employment growth between 1998 and 2000. Product innovations show a significantly positive effect on employment growth whereas process innovations showed a negative effect for German manufacturing firms. Also using 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.

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, on the firm level, process innovations play the more important role whereas on the sector level it is the product innovations that are more important. Real panel analyses over a longer time horizon are the contributions of Smolny (1998), Flaig and Rottmann (1999), van Reenen (1997) and Rottmann/Ruschinski (1997). 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 English innovation database of the SPRU (Social Policy Research Unit). 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 (1997) carried out analyses with data from the Ifo Institute. The authors show, in their analysis of the effects of technological change on employment growth, the importance of controlling for unobserved firm heterogeneity and adjustment processes. Controlling for these effects the authors find significantly positive effects of product innovations and significantly negative effects of process innovations on employment growth. An additional important variable in their models is the expected demand growth, which shows a positive effect on employment. Building on these results the authors also use a dynamic panel method, the Anderson-Hsiao framework (Rottmann and Ruschinski 1998). The positive effect of product innovations was also found in this analysis, but process innovations showed no significant impact. Flaig and Rottmann (1999) control for unobserved firm heterogeneity and estimate a recursive equation model with output, output expectations and employment as endogenous variables. They also find positive effects for product and process innovations. All these studies, even the panel studies, are restricted to a relatively limited time horizon. In addition, 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 on applying a different estimation strategy.

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

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

where L is labour demand, T is a measure for the technology used in the production process, Q is a measure for the quality of the product and X denotes other control variables, which we specify in more detail in equation (3). In our analysis we concentrate on the growth rates and thus transform the function: First, we take log values (denoted by lower case letters) and second, we first difference the equation (denoted by the difference operator Δ). This procedure basically is a first-difference panel approach, by which we also already account 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:

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

For the estimation of equation (2) we need a measure for the progress in the applied technology and for the improvement in the product quality. These changes 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. Substituting Δt and Δq with our innovation variables and introducing additional control variables on the sector level we get the following estimation equation:

$$\Delta l_{it} = \beta_0 + \beta_1 I^{Pc}{}_{it} + \beta_2 I^{Pd}{}_{it} + \beta_3 \Delta w_{it} + \beta_4 \Delta g_{it} + u_{it} \qquad (3)$$

I^{pc} denotes the process innovations and I^{pd} denotes the product innovations. Δw and Δg are additional control variables at the sector level (NACE two-digit classification). Δw denotes the growth rate of the real hourly wage rate, which of course may influence the employment demand of a firm. Since the wage rate of the individual firms are not observed, the average sectoral real hourly wage rate is used here as the best proxy available. Δg denotes the growth rate of the Gross Value Added in the sector and is included as a control variable for the demand situation in the respective sector.

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 very complex topic (Hamermesh and Pfann 1996), especially within small firms. 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 labour market. Assuming that innovations do not show their effects on employment growth in a short time horizon, i.e. from year to year, we apply these estimation technique and calculate averages over four and five year periods.[3] We then use these periods as time units in our panel estimations. That means the time index t in our estimation equation does not denote a single year anymore but a whole time period. The values of the variables are the calculated averages per period. So Δl_{it} stands for the average yearly employment growth rate per firm within one period. I^{pc} and I^{pd} are 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. Δw and Δg are averages of the yearly growth rate per period, but on a sectoral level. Additionally we introduce the variable e_{it}, which denotes the log of the employment start level of a firm in the respective four and five year period.

$$\Delta l_{it} = \beta_0 + \beta_1 I^{Pc}{}_{it} + \beta_2 I^{Pd}{}_{it} + \beta_3 \Delta w_{it} + \beta_4 \Delta g_{it} + \beta_5 e_{it} + u_{it} \tag{4}$$

e_{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 and Almus / Nerlinger 1999). 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) are there 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 labour 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 took first differences of

[3] 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. 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 former West Germany; all data since 1991 refer to Germany. We also tested several other lengths of periods; details are described in chapter 5.2.

our estimation equation. If there is no autocorrelation in the error terms, the only factor leading to an endogeneity problem might be a contemporaneous correlation of the innovation variables with the error term u_{it}, resulting from a shock simultaneously affecting employment and innovation. In case that such a shock occurs, a possible solution of this problem in our estimation strategy would be an instrumental variable strategy. 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. Second, thay are asked for their innovation expenses. But the construction of these instruments leads to additional problems. Beside the question of whether these instruments are uncorrelated with the error term, the construction of the survey questionnaire raises some concerns: The information on innovation impulses and innovation expenses is only available for those firms that introduced any innovation. Therefore we have to make questionable assumptions for those firms that did not introduce any innovations: For all those firms we have to replace the missing information in innovation impulses and innovation expenses by the value zero as a best approximation. But, using this strategy, our results did not show robust results. Either the instruments used showed a low explanatory power of the innovation variables or the exogeneity assumption was rejected by Sargan tests.[4]

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 every year, including eastern 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. The observation unit of this survey is not necessarily always a whole firm. For firms, that produce more than one product, the questionnaire refers only to a certain product range, i.e. for multi-product

[4] Results are not presented but are available from the authors on request.

firms the survey delivers even more detailed data than firm level data. For reasons of clarity, in the following we use the expression "firm" as the cross-sectional unit, even if it might not be correct in the case that there are different product ranges from one firm in the sample. This survey gives us a total sample of 33,159 observations from 7,023 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 as required by the 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/Wößmann (2004). In addition to the simple innovation dummy variable we also try to increase the explanatory power of this innovation variable by introducing different categories of innovations. We use different questions relating to the "importance" of an innovation. These questions give information on whether R&D was necessary for the implementation of a new innovation and if any patent applications were filed during the innovation process.

4.2 Descriptive statistics

The dataset consists of an unbalanced panel with 33,159 observations, collected from 7,023 firms over the 22 years 1982-2003. The survey is conducted among German manufacturing firms. 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 the descriptive statistics according to the observation units in our regressions, which are the averaged 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 of calculating growth rates, 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. Table 1 shows the descriptive statistics.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Employment growth (Δlog)	-0.016	0.261	-2.708	2.996
Innovation	0.497	0.412	0	1
Product innovation	0.406	0.410	0	1
Process innovation	0.317	0.365	0	1
Employment start level (log)	4.682	1.506	0	11.513
Sectoral GVA growth	0.005	0.046	-0.265	0.283
Sectoral real wage growth	0.018	0.026	-0.231	0.428

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

The mean of the dependent variable – the average yearly employment growth rate per period – shows a negative sign. That means, on average, the employment level in the firms of our sample is slightly declining within a period. This growth rate is measured as the difference in log values divided by the respective length of the period ((log L_T – log L_1)/T).[5] The innovation variable is the average of how often a firm responded with "yes" to the question of whether an innovation was introduced during a four or five year period. Thus, a firm that has innovated in all years has an innovation value of one, a 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. 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. The employment start level, which is the number of employees in the first year of a period is, on average, about 108 employees (or 4.682 in log values). The next two variables of table 1 are calculated as the average yearly growth rates within the corresponding period. The growth in the gross value added is added on the industry sector level to accounts for economic development of the corresponding sector. The mean value is slightly positive. Also as a control variable we include the sectoral real wage rate growth, which is also positive in our sample.

5. Results

In this section we present the results of several specifications of estimating equation (4). In section 5.1 we only distinguish between product and process innovations, in section 5.2 we present results for different firm sizes and different regional locations of the firm. In section 5.3 we introduce different categories for both types of innovation.

5.1 Product and process innovations

Table 2 presents the specifications 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.

[5] Log L_T denotes the log of the employment level in the last year observed during a period, log L_1 denotes the log of the level of employment in the first year observed during a period and T denotes the time between the first and the last year observed during a 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	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. Specification (1) shows standard OLS standard errors, specification (2) corrects for possible heteroskedasticity and specification (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 within firms, as in specification (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. The sectoral gross value added growth rate shows a positive sign and is significant at the 5% level. This is no surprise since it shows that a single firm benefits from the sectoral development. The wage growth has a negative effect on the employment level. 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. This result is clearly in line with theory that high wages hinder employment growth. 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.[6]

The variables of main interest, however, are the innovation 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 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 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 product innovations it is even higher at 5.7%, both being significant at the 1% level. This result is in line with the results of Greenan and Guellec (2000), who also found that process innovations lead to higher employment growth than product innovations on the firm level.

5.2 Robustness and heterogeneity of the effects

First we test the stability of our results with respect to the chosen lengths of the estimation periods – from 3-year intervals to 9-year intervals. 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 behaviour as in our preferred model described above. In the following, we therefore stick to the models with four- and five-year periods.[7]

Our first interest lies on 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.[8]

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[6] Table A1 in the Annex replicates the results of specification (3) in table 2, but also shows the effects for the dummy variables. They are only presented once since they remain almost unchanged in the different 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.

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

[8] Results are very similar if we set the cut-off point at 500 employees. We also tested splitting the sample in more detailed size classes, but the qualitative results remained stable.

Table 3: Different firm sizes

Dependent variable: average yearly employment growth

	(4) Fewer than 200 employees		(5) 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	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 (4) 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 effect any more. For larger firms (specification (5)), 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 (4) – 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 in line with earlier findings in the literature, that Gibrat's Law does not hold in the manufacturing sector (see Section 3). Also, if we look at the size of the effect, we are in line with other work. 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 subsample of large firms. 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. 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.

Another distinction can be made if 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 4 we distinguish in the location of the firm.

Table 4: Different regions

Dependent variable: average yearly employment growth

	(6) 1991-2003		(7) West 1991-2003		(8) 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	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 (6) presents results for between 1991 and 2003 (this refers to all off 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 western part of Germany (specification (7)) 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 (8)) 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.

5.3 Categories of innovation

In this section we will further exploit the detailed questions about the innovation behaviour of the Ifo Innovation Survey questionnaire and introduce different innovation categories. 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 5. In specification (9) we only split in innovations, innovation with R&D and innovations with patent applications (without distinction in product and process innovation). In specification (10) we split both in the importance and in the type of innovation.

Table 5: Different innovation categories

Dependent variable: average yearly employment growth

	(9)		(10)	
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	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. The interest in these results is in the different innovation variables. In specification (9) we introduce 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 (10) we split the innovation categories also 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 only weakly significant. 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. Only 2.3% of our sample introduced process innovations with patent applications whereas 19% introduced product innovations with paten applications.

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. But in eastern German firms only product innovations have had positive significant effects on employment growth; the effect of process innovations is still positive, but not significant. In large firms only process innovations have a significant effect. 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. 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.

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Annex

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)
Norh 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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