Effects of Innovation on Employment: A Dynamic Panel Analysis

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Abstract

This paper estimates the effect of innovation on employment on the firm level. Our uniquely long innovation panel data set of German manufacturing firms covers more than 20 years and allows us to use various innovation measures as required by theoretical models. We can distinguish between product and process innovations as well as between innovation inputs and innovation outputs. Using dynamic panel GMM system estimation we find positive effects of innovation on employment. This result is robust to the use of product and process innovations as well as for innovation input and output.

JEL Classification: O30, L60, C23, J23

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1. Introduction

1.1 The Issue

This paper estimates the effect of innovation on employment at the firm level in a dynamic panel framework. The direction of this effect remains unclear in theoretical analyses and calls for an empirical approach. Using a uniquely rich dataset for German manufacturing firms for the years 1982-2002 our estimation method allows us to control for unobserved firm heterogeneity, for possible endogeneity of the innovation measures with respect to employment and for potential dynamic effects.

Theoretical contributions analyzing the effect of innovation on employment at the firm level stress the importance of a distinction between product and process innovations.[1] But for both types of innovation, the effects on the labor demand of a firm are not clear. Product innovations lead to new products on the market which stimulate a new demand. This increasing demand allows innovating firms to hire more workers. Thus, from the direct effect of product innovations on employment we would expect a positive relationship. But there is also a less obvious indirect effect: If a firm introduces a product which is new to the market, there are no direct competitors yet and thus the innovating firm profits from a temporary monopoly position until other firms introduce similar or better products. In this market position the firm can exploit its monopoly power and maximize its profits which can lead to a reduction in output and thus also to a reduction in employment. This effect is in the opposite direction to the direct effect. Furthermore, if the new products are substitutes for existing products of the firm, the effect is not clear. New workers could simply replace old workers. Even a decrease is possible if the production of the new products requires fewer workers than the old products. Thus the overall effect of product innovations on employment are unclear in theory.

For process innovations the direct effect is very obvious. A process innovation is an improvement in the production process, which aims at making workers more productive. So the firm is able to produce the same level of output with less workers. We would therefore expect a negative effect of process innovations on employment. But we also have to consider an indirect effect here. The firm can produce its output at lower costs after the implementation of the process innovation. If this cost advantage is passed on to the prices of the goods, the demand for these goods should increase and this increased output allows

[1] See e.g. Katsoulacos (1986), Stoneman (1983), Hamermesh (1993), or for an overview Petit (1995).

the firm to hire additional workers. These effects make it not possible to draw a definite conclusion about the direction of the effect of process innovations on labor demand.

1.2 Previous Empirical Literature

These unclear results from theory are the reason why much empirical work was done to analyze the effects of innovation on employment on the firm level. Another strand of literature deals with the same question on the industry or macro level. But, in this study we want to concentrate our analysis on the firm level. A detailed overview of the existing literature is given Chennels and Van Reenen (1995).

First studies were, due to data availability, mostly cross-sectional analyses. Entorf and Pohlmeier (1990) and Zimmermann (1991) analyzed German micro data. Entorf and Pohlmeier (1990) found a positive effects for product innovations, while process innovations showed no significant effects. Zimmermann (1991) concludes that technological progress was important for the employment decrease in 1980, thus finds a negative effect of innovation. But the definition of innovation he used refers to a question which asks explicitly for the implementation of labor-saving technological progress. Blanchflower and Burgess (1999), however, find a positive relation between process innovation and employment growth using innovation surveys from the UK in 1990 and Australia in 1989/1990.

Newer studies use two or more points in time, which allow the authors to analyze growth rates, a methodology which eliminates the unobserved firm heterogeneity. Brouwer et al. (1993) were using two innovation surveys for the Netherlands to estimate the effects of innovation on employment growth rates. They find a negative effect for overall R&D investments, but a positive effect for product related R&D. Greenan and Guellec (2000) use a French innovation survey of 1991 for analyzing employment growth during the period 1986 to 1990. They find positive effects of both, process and product innovation with the effect for product innovations being higher.

In this line are also recent studies that use the harmonized European innovation survey, the Community Innovation Survey (CIS). With this survey comparable innovation data for different countries are available. Using these data sets there exist single country studies, e.g. Jaumandreu (2003) using Spanish data, Peters (2004) using German data, but there also exist comparative studies like Harrison et al. (2005). Jaumandreu (2003) develops a specific model for the use of CIS data. Using Spanish CIS3 data of the year 2001 he finds that process innovations are not responsible for net employment displacement and that product innovations lead to a positive employment growth. Peters (2004) employs this model for Germany, extending the research to the service sector. For the manufacturing sector, she also finds positive effects of product innovations, where there is no significant difference in the size of the effect between products new to the market or products imitated by the innovating firm. For process innovations, Peters finds a negative effect on employment growth, mainly for rationalization innovations. Harrison et al. (2005) compare CIS3 data for France, Germany, Spain and the UK. Overall the effects in the countries are quite similar showing again positive effects of product innovation on employment growth and showing that displacement and compensation effects of process innovations are present in the manufacturing sector. For the service sector results are less clear, e.g. in Germany product innovations seem to be related with negative employment effects.

With the increasing availability of innovation data panel studies were undertaken more often. Smolny (1998) analyzes the relationship of innovation, prices and employment for Germany. He finds a positive effect of product as well as process innovation on employment. Lachenmaier and Rottmann (2006) estimate a static panel approach and also find significant effects for both types of innovation.

The studies most relevant for our work are van Reenen (1997), Rottmann and Ruschinski (1998) and Piva and Vivarelli (2004, 2005), as they allow for an adjustment process by including lagged values of employment. Rottmann and Ruschinksi (1998) use the Ifo Business Survey of the years 1980 to 1992. Using an Anderson-Hsiao dynamic panel approach the authors also find positive effects of product innovation, but no significant effect for process innovations. Van Reenen (1997) analyzes UK data matched with major innovations counted by the Science and Technology Policy Research Unit (SPRU). Controlling for fixed effects, dynamics and endogeneity he finds a positive causal effect of product innovations on employment. Unfortunately, his selection of firms is restricted to firms listed at the London stock exchange. Also his measure of innovation differs from ours, as the SPRU innovation counts refer only to the major, most influencing innovations and does not measure small innovative progress. A similar model is estimated by Piva and Vivarelli (2004, 2005) for Italy using gross innovative investment as the innovation variable. Using GMM system estimations they find small but significant effects for technological change.

1.3 Overview

To sum up, most studies found a positive relationship between product innovations and employment whereas the effect of process innovations leads to different results in the literature. We will contribute to the existing literature by using a dynamic panel framework for a uniquely long innovation data set with different innovation measures for the German manufacturing sector. As the most recent studies, we control for unobserved heterogeneity, the possible endogeneity of the innovation variable and for dynamic effects in the employment adjustment process. In addition, we have very detailed information about the innovations introduced. We can distinguish between input (innovation expenditure) and output (innovations introduced) variables of the innovation process for this long period. The innovation output variable can be split up further to distinguish between process and product innovations and the in the importance of innovations. The paper is structured as follows. Section 2 presents the model and our estimation method. In Section 3 we describe the database. The results are presented in Section 4, Section 5 concludes.

2. The Model and Econometric Modeling (preliminary)

2.1 The Employment Demand Equation

We start our econometric modeling with a standard static employment equation.

$$n_{i,t} = \beta_1' X_{i,t} + \gamma_i + \varepsilon_{i,t} \qquad (1)$$

n denotes the logarithm of the employment level of firm i at time t, X is a set of variables that determines employment and − in our analysis − includes for example innovation variables. γ_i is an unobserved firm-specific time-invariant effect which may be correlated with the variables in X. $\varepsilon_{i,t}$ is the error term with $\varepsilon_{i,t} \sim iid(0, \sigma_\varepsilon^2)$. However, a static estimation equation might lead to some problems. The high costs of hiring and firing is a well-known argument for costly employment adjustment, especially in European economies. If firms face these high costs, the actual employment will deviate from the equilibrium level in the short run. The short-run dynamics compound influences from adjustment costs, expectations formation and decision processes. Therefore, a dynamic panel data model is considered that includes unrestricted lag structures in order to model the sluggish adjustment.[2]

$$c(L)n_{i,t} = \beta'(L) X_{i,t} + \gamma_i + \varepsilon_{i,t}, \qquad i = 1,...,N, \text{ and } t = 1,...,T. \qquad (2)$$

[2] See Baltagi (2005) for a introduction of the econometrics of dynamic single equation panel data models.

Here *c(L)* denotes the corresponding polynomial in the lag operator *for* $n_{i,t}$.[3] We also include lagged values of the innovation variables in *X* to account for a time lag between the implementation of an innovation and its effect on employment. Therefore *β(L)* is a vector of associated polynomials in the lag operator for the vector $X_{i,t}$.

This estimation approach then leads to the following estimation equation. We already include in this equation the respective number of lags that were suggested by test statistics during the estimation process.

$$n_{it} = \beta_1 n_{i,t-1} + \beta_2 n_{i,t-2} + \beta_3 I_{it}^{Pd} + \beta_4 I_{i,t-1}^{Pd} + \beta_5 I_{i,t-2}^{Pd} + \beta_6 I_{it}^{Pc} + \beta_7 I_{i,t-1}^{Pc} + \beta_8 I_{i,t-2}^{Pc} + \beta_9 w_{it} + \beta_{10} d_{it} + \gamma_i + \varepsilon_{it} \tag{3}$$

So *X* includes in our base specification two lags of employment *n,* product innovation I^{Pd} and process innovation I^{Pd} and two lags of each innovation variable. Additionally we include several control variables. These are either simple dummy variables for the NACE 2-digit industries and years. In our base specification above we include continuous control variables at the industry level. We control for the average industry-wide real hourly wage rate *w* and for the industry-level Gross Value Added *d* which is included as a proxy variable for demand in the respective industry.

2.2 Estimation Approach

The next question is how to estimate Equation (3). Simple OLS estimation of this dynamic model will lead to biased results in the presence of unobserved heterogeneity. The lagged dependent variables are correlated with γ_i. One can show that the OLS estimates for the lagged dependent variables are biased upwards. To eliminate these firm effects γ_i the standard approach is to use the within estimator (often called fixed-effects estimator). This estimation strategy uses the demeaned estimation equation. But, the transformed variables $\left(n_{i,t-1} - \overline{n}_{i,t-1}\right)$, where $\overline{n}_{i,t-1} = \frac{1}{(T-1)} \sum_{t=2}^{T} n_{i,t-1}$, will still be negatively correlated with $\left(\varepsilon_{i,t} - \overline{\varepsilon}_i\right)$. This leads to a downward bias of the estimated parameters of the lagged dependent variables, even if the $\varepsilon_{i,t}$ are not serially correlated. Including more regressors does not remove the bias. Only if $T \to \infty$ the within-estimator will be consistent for the dynamic panel data model. However, T is typically small in micro panel data sets.[4]

[3] For stability of the dynamic equation the inverses of all roots of the lag operator polynomial *c(L)* must be insides the unit circle.

[4] See Hsiao (2003), ch. 4.

For this reason one uses the first-differenced equation to eliminate the firm fixed effect. After this transformation there are instruments for the lagged differenced dependent variable ($\Delta n_{i,t-1}$) available to avoid the correlation with the error term. There exist various suggestions for such estimators, differing in the instruments used. The estimator proposed by Andersen and Hsiao (1982) uses one further lag (either as level or as difference) as instrument for $\Delta n_{i,t-1}$. Holtz-Eakin et al. (1988) and Arellano and Bond (1991) replace the IV estimation technique by GMM estimation, in which the instrument matrix includes all (or at least more) previous levels of the lagged dependent variable. This is why this strategy is also called GMM difference estimation.

The strategy we will use in our study is known as GMM system estimation and was proposed by Blundell and Bond (1998). The authors have shown in Monte Carlo studies that this estimator behaves better than the GMM difference estimator especially in two cases: First, in short sample periods, and second, and more important for our study, it behaves better if the variables are persistent over time. If the evolution of a variable is highly persistent, the correlation between the variable in differences and its past values in levels will disappear. Therefore the instruments will be weak. In these cases the GMM difference estimator for the lagged dependent variable is also biased downwards, in the same direction as the within group estimator. The GMM system estimator extends the model by estimation a system of first-differenced equations and the equations in levels. In the first-differenced equations we use as instruments the lagged level values of the variables as in the GMM difference estimator. In the levels equations one uses differences as instruments. These instruments are valid if there is orthogonality between ΔX_{it} and ε_{it}.[5] The validity of the additional instruments can be tested by a Sargan difference test between the GMM difference and the GMM system model.

It has been shown that the two-step estimates of the GMM difference and GMM system standard errors have a downward bias. Therefore we apply the finite-sample correction for the asymptotic variance of the two-step GMM estimator (Windmeijer 2005).

Knowing the direction of the biases in the OLS estimator, the within groups estimator and the Arellano-Bond estimator, these regression methods give us upper and lower bounds of where we would expect the estimation coefficient to lie in between. As we will show in our results section after the description of the database this is also true in our study.

[5] As instrument for the lagged dependent variables one can use $\Delta n_{i,,t-1}$ if we treat the lagged dependent variable as predetermined.

This estimator also allows us to address the problem of potential endogeneity of innovation. Since we measure employment and innovation both at the firm level, it is very likely that these variables are chosen simultaneously. Thus we would not estimate the causal effect in simple estimation methods. In dynamic panel estimations, however, one can also instrument the potential endogenous variables. This is done, similar to the lagged dependent variable, by using the appropriate lags as instruments of the variables.

3. Database and Descriptive Statistics

3.1 The Ifo Innovation Survey

For our analysis we use survey data stemming from the Ifo Innovation Survey, a survey which is conducted yearly by the Ifo Institute for Economic Research in Munich, Germany. This survey covers the German manufacturing sector. The uniqueness of this data set is the very long time horizon for which detailed innovation data is available. The survey was started in 1982, in 1991 − after the German reunification − firms from former East Germany were included and the survey is still ongoing. For this paper we use the data up to the year 2003, which describes firms' behavior in 2002.[6]

Each year the information of in average 1500 respondents are collected. Most questions in the questionnaire are related to the innovation behavior in the preceding year. The discussion of how to measure innovations correctly is still ongoing. In an innovation survey manual published by the OECD and Eurostat the importance of using innovation input and innovation output measures is stressed (OECD and Eurostat 2005). With the Ifo Innovation Survey we can deal with both types of innovation measures: First, we can use questions whether any innovations were introduced and how important they are. Second, we can use the innovation expenditure which reflects the input to the innovation process.[7]

Our first measure is the question of whether any product innovations were introduced to the market or whether any process innovations were implemented in the production process. In addition we can obtain further information on the importance of an innovation. One question refers to whether the implemented innovations required R&D. Another type of the importance are those innovations for which any patent applications were filed during the innovation process. Patent applications are very expensive and so we expect that only

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[6] More detailed information about the history and the methodology of the Ifo Innovation Survey can be found in Penzkofer (2004).

[7] A more detailed comparison of the innovation measures of the Ifo Innovation Survey with other common innovation measures can be found in Lachenmaier and Wößmann (2006).

for few important innovations, for which the firms expect high returns, patent applications are filed.

Our second measure, the innovation expenditure includes all R&D expenses of the innovation process but also costs for licenses, patenting and other costs that emerged during the implementation of new products or processes. It is measured as the share of innovation expenditure in total sales of a firm.

In addition to the detailed innovation measures the survey collects information about other firm characteristics. An important information, which we will use as the dependent variable in the regression analyses, is the number of employees in a firm. Unfortunately the data set does not contain additional information on whether these workers are full-time or part-time workers or how many hours they work. Since we expect the effects to differ between different industries we can also use the industry classification in the questionnaire, which can be classified according to the NACE 2-digit level. By using these control variables and the additional use of year dummy variables we also hope to control for much of the variation in working hours. We thus control for an overall trend towards or away from one type, but also for differences in the structure of workers between industries.

Unfortunately, we do not get any information about wages in the firms. But, to be able to control for the variation in wages over our time period we include the real hourly wage rate within a 2-digit industry as we can obtain this information from the National Statistical Office as the best approximation. Also from this source we take the Gross Value Added (GVA) within a 2-digit industry. This can serve as a proxy for the demand in the respective industry.

3.2 Descriptive Statistics

We use the Ifo Innovation Surveys of the years 1983-2003, containing information about firms' behavior in the years 1982-2002. The survey covers the German manufacturing sector. Merging all available yearly datasets leads to a complete sample of 31885 observations from 6817 firms. For our estimation strategy, which includes lagged variables and earlier values as instruments, we need at least four consecutive observations of a firm. For the correct calculation of the test statistics, however, we need six consecutive observations.

Dropping firms with less than six consecutive observations and dropping firms with missing values in the variables of interest reduces our estimation sample to 7536 observations from 1073 different firms. This might raise some concern about the representativeness of our sample. Table A1 in the annex shows descriptive statistics for the original sample and our estimation sample finally used. We see differences mainly for the employment and the innovation input variable. It seems that larger firms, which spend more on innovation tend to stay in the sample more often, what is reflected in the larger mean values in the estimation sample. As can be seen in Table A1 the average firm in our sample has a size of 654 employees. This number is driven heavily by the few very large firms. The median firm in our sample has 129 employees. In contrast when looking at the 25% percentile, the median and the 75% percentile we see smaller differences between the two samples. Thus we can suppose that there are few very large firms which affect the mean values very much. Therefore, we crosscheck all following estimations with a restricted sample excluding extreme outliers. This restricted sample shows an average value of 311 employees, if we exclude the lowest and the largest percentile of firms in terms of employees. Table A2 shows the distribution of the firms over different industries and size classes. The Table compares the estimation sample with the original sample from the Ifo Innovation survey. As we can see all industries and size classes are covered in our study.

Looking at the innovation variables in Table 1 we can use several questions of the Ifo Innovation Survey as innovation measures as described in section 3.1. The most simple one is the question whether the firm introduced any innovations during the preceding year. In our sample this was the case in 51.3% of all observations. Splitting up this variable in product and process innovations we see that more firms introduced product innovations (42%) than process innovations (33.5%). Allowing for differences in the importance of innovations the number of innovators reduces. Only 34.8% of the responses indicated the introduction of a new product for which R&D was necessary and only 22% reported a process innovation which required R&D. 19.6% of the respondents reported that a patent application went along with a product innovation and only 2.6% reported a process innovation with patent application. This very low number has to be kept in mind when interpreting the estimation results later.

For the innovation expenditure we had to reduce our sample because firms are very reluctant in answering this question. Since we need again six consecutive observations for a firm without missing values in the innovation variable, our sample is reduced to 4448 observations from 690 different firms. We created two different variables for the innovation expenditure. One is also a simple indicator of whether the firm reported any positive innovation expenditure at all for a certain year, the second are the real innovation expenses.[8] 47.3% of the respondents reported positive innovation expenditure. The mean of the innovation expenses is about 9 million Euros.

Table 2 shows two different employment variables for three groups of firms: firms that reported an innovation for all years in which they were observed (permanent innovators), firms that switched at least once between innovation and no innovation or vice versa (occasional innovators) and firms that never reported an innovation during their observation period (non-innovators). We find significant differences for these three groups. First it seems that it is mainly the large firms that innovate permanently. The mean firm size of permanent innovators is 1326, going down to 364 for occasional innovators and 125 for non-innovators. Perhaps even more interesting is the comparison of the average yearly growth rate of employment during the observation period: Permanent innovators grow with a average growth rate of 2.5% whereas occasional innovators in average almost stay at the same size and non-innovators shrink with an average growth rate of -2.3%. This can be interpreted as a first descriptive evidence for a positive impact of innovations on employment at the firm level.

4. Results

4.1 Basic Results

This section presents the results of our estimations. In our first result table (Table 3) we show the results for simple AR(2) regressions of the employment variable to compare the different estimation methods presented in Section 2. Because the lags of a higher order than two are not significant, we present the results for the different estimation methods for the AR(2) process only.

As one can easily see in Table 3, the coefficients behave exactly as expected. The estimators of the lagged dependent variables add to an estimator of 0.982 for the OLS model in Specification (1), 0.383 in the fixed effects model of Specification (2), 0.475 in the GMM difference model in Specification (3) and 0.838 in the GMM system estimation in Specification (4). This confirms the expected directions of the bias of the lagged dependent variables. In the OLS model the estimates are biased upwards, in the Fixed Effects and the GMM difference model the estimates are biased downwards. The estimates

[8] Real values are calculated using an industry specific deflator. From the German Statistical Office, Gross Value Added is available in current and constant prices on industry level. We use this information for the construction of the deflator.

in the GMM system estimation lie in between the upper bound of the OLS model and the lower bound of the Fixed Effect and the GMM difference model.

Table 4 shows the results of our main specifications, where we use the simple product and process innovation dummies as our innovation measures. In both specifications the test statistics support the validity of our estimations. The Sargan test does not reject our instruments used, the AR(2) test does not reject the null hypothesis of no second-order serial correlation.[9] We also tested for the validity of the additional instruments in the GMM system model compared to the GMM difference model as proposed in Blundell and Bond (1998). The difference in Sargan test does not reject the validity of the additional instruments in the GMM system estimation compared to the GMM difference estimation.[10]

Specification (5) to (7) differ in the use of dummies for industry sectors and years. Specification (5) shows the results without dummy variables for industry and year, Specification (6) includes year dummies to control for any technology shocks that are common for all firms, and Specification (7) includes year dummies and industry dummies. The choice of the specification only affects the control variables itself and has no relevant impact on the innovation variables. In Specification (5) the sector variables for real hourly wage rate and Gross Value Added (GVA) show both significant effects as expected. The wage rate has a significantly negative effect on employment whereas the GVA as a proxy for the demand shows a significantly positive effect. In Specification (6), which includes year dummies, only the GVA remains significant. The significance of the wage rate is taken away in the year dummies. In Specification (7) both the wage rate and the GVA are not significant anymore. Since the year dummies are jointly significant, but sector dummies are not we decide to stick to the specification with year dummies only as the sector effect seems to be captured well by the GVA (Specification (6)).

The coefficients of the lagged dependent variable confirm the importance of including these effects. In all three specifications the effect is quite similar. In Specification (6), our preferred model, we find a significant effect of 0.740 for the first lag and a significant effect of 0.141 for the second lag. A test for the sum to be one is rejected, which supports the stability of the model.

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[9] The significant first-order correlation of the errors is induced by first differencing the data. If the errors $\varepsilon_{i,t}$ are i.i.d. with variance σ^2 for the corresponding first differences we get: $E(\Delta\varepsilon_{i,t}\Delta\varepsilon_{i,t-1}) = -\sigma^2$ and $E(\Delta\varepsilon_{i,t}\Delta\varepsilon_{i,t-2}) = 0$. Therefore, we must use the relevant test whether the errors in first differences are AR(2) or not.

[10] The test statistic for our baseline specification (6) is 55.78 with 58 degrees of freedom resulting in a p-value of 0.558. Specifications (5) and (7) show qualitatively the same results.

The innovation variables also show significantly positive effects. Before analyzing the results in more detail it is interesting to look at the treatment of the innovation variables. Variables which are not strictly exogenous can be either treated as predetermined or endogenous in the GMM system framework. This distinction defines which instruments are valid.[11] Since in the model treating innovation as endogenous the set of moment conditions is a strict subset of the set of moment conditions in the model treating innovation as predetermined we can use a difference in Sargan test to test the validity of the additional instruments in the model with predetermined innovation. This test shows that the model treating innovations as predetermined is rejected at the 5% level (p-Value=0.044). Thus, in the following specification we will treat innovation as endogenous.

Next we will turn to the analysis of the innovation variables. As for product innovations we can see that only the second lag of product innovations shows a weakly significant positive effect on employment. This result is surprising since most studies find a positive effect for product innovation and a positive effect would be expected as the direct effect from theory (cf. Section 1). Our explanation for this result is that the definition of the innovation in the Ifo Innovation Survey might be responsible for this result as it includes also very small innovations. We will test in later specifications how the more important innovations affect employment.

Process innovations, however, show a clearly positive effect on employment. Again it is the lagged variables that show significantly positive effects, but for process innovations it is the first and the second lag. Also, the effects are higher than those estimated for product innovations. This result supports the hypothesis that the indirect effects of process innovations are present and firms pass on the productivity gains to lower the prices and thus increase demand and employment. This significantly positive effect was not clear from a theoretical point of view, but is in line with some previous studies (e.g. Blanchflower and Burgess 1999 or Greenan and Guellec 2000). In addition, it is interesting that we find a higher effect for process innovations than for product innovations. This was only found in few studies (e.g. Greenan and Guellec 2000, Lachenmaier and Rottmann 2006).

We also carried out different tests for joint significance. Testing for joint significance in Specification (6) for all product innovation variables also does not show a significant

[11] If we treat innovation as predetermined we can use variable levels dated from period one up to period t-1 as instruments for the first differenced equations and differences from period two up to period t as instruments for the level equations. If we treat innovation as endogenous valid instruments stop one year earlier (i.e. at period t-2 for the first differenced equation and at t-1 for the levels equation).

effect whereas process innovations are jointly significant at the 5% level. Testing for joint significance for product and process innovations in the different lags shows that the contemporaneous innovation variables are jointly insignificant whereas both the first and second lag are jointly significant at the 5% level.

As mentioned in Section 3.2 we had to restrict our estimation sample to firms which have answered at least six consecutive years. Since this restriction leads to a larger share of large firms which stay in the sample, we tested our results for the robustness regarding extreme outliers. We dropped the lowest and the largest percentile of firms in terms of employees. It turns out that our results are not sensitive to the presence of outliers. Regression results are very similar to the whole sample. Especially the coefficients of the innovation variables remain almost unchanged. We also tested deeper lags of innovations. But these deeper lags were not significant in any specification.

4.2 Results Using Different Innovation Measures

In Table 5 we use different innovation output measures. In Specification (8) we replace the simple innovation variables by those for which the firms responded that R&D was necessary. But, the results are for both types of innovations quite similar to those of Specification (6) with the simple innovation indicators. Again, for product innovations it is only the second lag which shows a significant effect, whereas for process innovations it is the first and the second lag. Also, as for the size of the effects, results are very similar to the estimates before. Joint significance test also show the known results from Specification (6). Product innovations are jointly insignificant, process innovations are jointly significant. The contemporaneous variables are jointly insignificant whereas both first (at 5% level) and second lags (at 1% level) are jointly significant.

Specification (9) uses those innovations which went along with patent applications. We have to keep in mind that the number of firms with process innovations with patent applications is very low (see Table 1), so these results should only be interpreted with caution. As we can see from the results, the standard errors for process innovations are indeed quite high which might be a reason for not finding significant effects. For product innovations we find in this specification highly positive and significant effects. Especially the contemporaneous variable shows a high effect on employment. This confirms our hypothesis that the high costs for patent applications are only invested for very promising innovations for which high returns are expected. Joint significance test in this specification show no significance for process innovations. Product innovations show a jointly significant effect at the 1%level, process innovations are also jointly significantly positive, although only at a 10% level. As far as the lag structure is concerned, the contemporaneous variables and the second lag variables are each jointly significant.

In Table 6 we replace the innovation output variables used so far by variables which measures the input into the innovation process. Results are shown for different measures of the innovation input. Unfortunately, not all firms respond always to the question relating to innovation expenditure. So, our sample is reduced again, in this case to 4448 observations from 690 firms. When using innovation expenditure as explanatory variable one practical problem arises. Ideally, we would like to include innovation expenditure also in log values. However, simply taking the log would lead to the loss of all firms which have zero innovation expenditure, i.e. all non-innovators. Thus we test two different specifications. In Specification (10) we replaced the original innovation expenditure by one plus the original value. This leads to a zero value after taking the logarithm. This method is sometime used in these cases, but does not distinguish anymore between innovators and non-innovators by replacing zero innovation expenditure with low positive values.[12] Results show a significantly positive effect for the second lag of innovation expenditure. This is no surprise since we would actually expect a longer time lag between the innovation expenditure and its effect on employment than for innovation output measures and their effects. It can take some time from the beginning of an innovation to the implementation in the firm or the introduction to market. Since we classify all firms as innovators in Specification (10) we again have a look at the distinction between innovators and non-innovators in Specification (11). Here we include a dummy variable which is one for all firms that reported any positive innovation expenditure and zero otherwise. Again, we find a significantly positive effect of the second lag.

So, to sum up, almost all of our innovation measures show a significantly positive effect on employment. Surprisingly, this effect is higher for process innovation than for product innovations. Process innovations usually show their effect on employment faster than product innovations. Especially product innovations for which patent applications were filed show a very high effect. As for the input variables it raises some concern about the exact specification but the different possibilities lead to very similar results showing also a significantly positive effect.

[12] We also tested other values than one. We used 0.01, 0.1 and the minimum value for this variable of other firms. However, results are very robust to the choice of the value that we use for replacing.

5. Conclusions

The effect of innovation on employment remains unclear in theoretical contributions. This has given reasons to address this question empirically. With an upcoming data availability it is today possible to estimate the effects at the firm level, on which the decision to innovate or not takes place. Our uniquely long panel data set, covering more than 20 years, offers detailed information about the innovation behavior of German manufacturing firms. We have data available for innovation output and innovation input measures. Innovation outputs are measured by information about introduced or implemented innovations. Innovation input is measured by innovation expenditure. As for innovation output, we can distinguish between product and process innovations, as it is necessary relying on theoretical analyses. In addition, the innovation output can further be divided into several categories reflecting the importance of innovations. To control for unobserved firm heterogeneity, endogeneity of innovation with respect to employment and dynamics we employ a dynamic panel analyses. The effects are positive and robust to several specifications. The effect for process innovation tends to be higher than the effect for product innovation. We find significant effects mostly for the first or second lag, except for product innovations with patent applications which also have an contemporaneous effect on employment. Innovation inputs are also significantly positive. For this measure we only find significant effects for the second lag of the variable. This gives further support to our innovation variables as we find a longer lag for the effect of innovation input on employment than for innovation output.

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Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment	7,536	654	4,317	1	99,999
Log Employment	7,536	4.870	1.553	0	11.513
Innovation	7,536	0.513		0	1
Product Innovation	7,536	0.420		0	1
Process Innovation	7,536	0.335		0	1
Product Innovation (R&D)	7,475	0.348		0	1
Process Innovation (R&D)	7,337	0.220		0	1
Product Innovation (Patents)	7,475	0.196		0	1
Process Innovation (Patents)	7,337	0.026		0	1
Innovation Expenditure (dummy)	4,448	0.473		0	1
Innovation Expenditure (in 1000 €)	4,448	8,883	107,645	0	2,601,066
Log Sectoral Gross Value Added	7,536	4.546	0.130	3.457	5.382
Log Sectoral Real Hourly Wage Rate	7,536	2.938	0.778	-0.083	4.157

Table 2: Descriptive Statistics According to Innovation Status

Variable	Obs	Mean	Std. Dev.	Min	Max
		Permanent Innovators			
Employment	197	1326	4539	17	49744
Avg. Yearly Employment Growth	197	0.025	0.137	-0.349	0.827
		Occasional Innovators			
Employment	685	364	1524	2	37033
Avg. Yearly Employment Growth	685	-0.001	0.089	-0.407	0.628
		Non-Innovators			
Employment	191	125	361	1	4099
Avg. Yearly Employment Growth	191	-0.023	0.092	-0.393	0.235

Table 3: AR(2) Process of Employment

	(1) *OLS*	(2) *FE*	(3) *GMM diff*	(4) *GMM sys*
Lag employment	0.723^{***} *(0.045)*	0.347^{***} *(0.050)*	0.379^{***} *(0.124)*	0.731^{***} *(0.149)*
2nd lag employment	0.259^{***} *(0.046)*	0.036 *(0.033)*	0.096 *(0.090)*	0.107 *(0.077)*
Constant	0.085^{***} *(0.019)*	3.004^{***} *(0.213)*		0.784^{*} *(0.405)*
Observations	7536	7536	6463	7536
Number of firms	1073	1073	1073	1073

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

Table 4: GMM System Estimation Results

	(5)		(6)		(7)	
Lag employment	0.744^{***}	*(0.088)*	0.740^{***}	*(0.081)*	0.753^{***}	*(0.062)*
2nd lag employment	0.130^{**}	*(0.061)*	0.141^{**}	*(0.056)*	0.146^{***}	*(0.050)*
Product Innovation	-0.004	*(0.046)*	-0.001	*(0.039)*	-0.008	*(0.040)*
Lag Product Innovation	0.012	*(0.014)*	0.013	*(0.013)*	0.015	*(0.013)*
2nd Lag Product Innovation	0.009	*(0.010)*	0.015^{*}	*(0.008)*	0.014^{*}	*(0.008)*
Process Innovation	0.018	*(0.032)*	0.038	*(0.034)*	0.026	*(0.031)*
Lag Process Innovation	0.025^{**}	*(0.010)*	0.023^{**}	*(0.009)*	0.020^{**}	*(0.009)*
2nd Lag Process Innovation	0.015^{**}	*(0.008)*	0.015^{**}	*(0.007)*	0.015^{**}	*(0.006)*
Real Hourly Wage Rate	-0.190^{***}	*(0.051)*	-0.132	*(0.083)*	-0.044	*(0.073)*
Gross Value Added	0.050^{***}	*(0.015)*	0.048^{***}	*(0.015)*	-0.029	*(0.030)*
Year Dummies	---		*incl.*		*incl.*	
Sector Dummies	---		---		*incl.*	
Constant	1.290^{***}	*(0.327)*	0.966^{**}	*(0.447)*	0.720^{*}	*(0.400)*
Observations	7536		7536		7536	
Number of firms	1073		1073		1073	
Sargan	*243 (205)*		*192 (207)*		*197 (206)*	
AR1	-2.780^{***}		-2.900^{***}		-3.047^{***}	
AR2	-0.640		-0.889		-0.983	

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

Table 5: Further GMM System Estimation Results

	(8)		(9)	
Lag employment	0.776***	*(0.072)*	0.667***	*(0.067)*
2nd lag employment	0.123**	*(0.050)*	0.187***	*(0.046)*
Product Innovation (R&D)	-0.005	*(0.046)*	---	
Lag Product Innovation (R&D)	0.013	*(0.018)*	---	
2nd Lag Product Innovation (R&D)	0.022*	*(0.013)*	---	
Process Innovation (R&D)	-0.014	*(0.044)*	---	
Lag Process Innovation (R&D)	0.033**	*(0.013)*	---	
2nd Lag Process Innovation (R&D)	0.029***	*(0.010)*	---	
Product Innovation (Patent)	---		0.221***	*(0.054)*
Lag Product Innovation (Patent)	---		0.000	*(0.018)*
2nd Lag Product Innovation (Patent)	---		0.034**	*(0.014)*
Process Innovation (Patent)	---		0.089	*(0.125)*
Lag Process Innovation (Patent)	---		0.052	*(0.056)*
2nd Lag Process Innovation (Patent)	---		0.103	*(0.075)*
Real Hourly Wage Rate	-0.038	*(0.076)*	-0.051	*(0.112)*
Gross Value Added	0.038***	*(0.013)*	0.038***	*(0.014)*
Year Dummies	*incl.*		*incl.*	
Constant	0.500	*(0.393)*	0.744	*(0.535)*
Observations	6963		6963	
Number of firms	1059		1059	
Sargan	193 (207)		177 (207)	
AR1	-2.926***		-2.935***	
AR2	-0.284		-1.654	

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

Table 6: GMM System Results Using Innovation Input Variables

	(10)		(11)	
Lag employment	0.833***	*(0.075)*	0.889***	*(0.066)*
2nd lag employment	0.087	*(0.063)*	0.062	*(0.059)*
Innovation Expenditure	0.010	*(0.009)*	---	
Lag Innovation Expenditure	0.002	*(0.004)*	---	
2nd Lag Innovation Expenditure	0.006**	*(0.002)*	---	
Innovation Expenditure (Dummy)	---		-0.004	*(0.015)*
Lag Innovation Expenditure (Dummy)	---		0.007	*(0.015)*
2nd Lag Innovation Expenditure (Dummy)	---		0.031***	*(0.011)*
Real Hourly Wage Rate	-0.064	*(0.108)*	-0.013	*(0.111)*
Gross Value Added	0.031**	*(0.014)*	0.033**	*(0.013)*
Year Dummies	*Incl.*		*incl.*	
Constant	0.499	*(0.549)*	0.160	*(0.540)*
Observations	4448		4448	
Number of firms	690		690	
Sargan	140 (134)		165 (152)	
AR1	-4.857***		-5.325***	
AR2	-1.463		-1.189	

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

APPENDIX

Table A1: Comparison of Estimation Sample and Original Sample

		Original Sample				Estimation Sample				
Variable	Obs	Mean	p25	Median	p75	Obs	Mean	p25	Median	p75
Employment	31,885	445	39	100	275	7536	654	45	129	353
Log Employment	31,885	4.659	3.664	4.605	5.617	7536	4.870	3.806	4.868	5.866
Innovation	31,420	0.494				7536	0.513			
Product Innovation	31,420	0.403				7536	0.420			
Process Innovation	31,420	0.315				7536	0.335			
Product Innovation (R&D)	30,995	0.329				7475	0.348			
Process Innovation (R&D)	30,488	0.195				7337	0.220			
Product Innovation (Patents)	30,995	0.190				7475	0.196			
Process Innovation (Patents)	30,488	0.023				7337	0.026			
Innovation expenditure (dummy)	24,978	0.512				4448	0.473			
Innovation expenditure	24,978	3,343	0	11.3	466	4448	8,883	0	0	438

Table A2: Distribution of firms in NACE 2digit Sector and Size Classes

		-49 employees	50-199 employees	200-499 employees	500-999 employees	1000+ employees	Total
15	M.o. food products and beverages	29 / 237	38 / 160	12 / 50	5 / 34	2 / 13	86 / 494
16	M.o. tobacco products	2 / 6	0 / 4	1 / 4	0 / 0	1 / 3	4 / 17
17	M.o. textiles	10 / 81	16 / 153	9 / 74	1 / 19	1 / 6	37 / 333
18	M.o. wearing apparel	14 / 91	10 / 77	5 / 21	3 / 8	1 / 4	33 / 201
19	Leather	4 / 49	7 / 61	3 / 15	0 / 2	0 / 0	14 / 127
20	M.o. wood and wood products	43 /232	14 / 82	3 / 19	0 / 5	0 / 2	60 / 340
21	M.o. pulp, paper	13 / 104	22 / 116	9 / 53	5 / 22	3 / 12	52 / 307
22	Publishing, printing	29 / 201	39 / 176	13 / 49	6 / 17	3 / 6	90 / 449
23	M.o. coke, fuel	0 / 2	0 / 1	0 / 3	0 / 5	2 / 7	2 / 18
24	M.o. chemicals	8 / 82	7 / 62	5 / 27	2 / 9	3 / 9	25 / 189
25	M.o. rubber, plastic products	20 / 231	27 / 207	8 / 62	7 / 21	3 / 16	65 / 537
26	M.o. no-metallic mineral products	23 / 192	33 / 151	29 / 75	6 / 30	3 / 18	94 / 466
27	M.o. basic metals	3 / 22	8 / 38	3 / 21	5 / 20	1 / 12	20 / 113
28	M.o. fabricated metal products	28 / 246	41 / 237	18 / 98	6 / 38	3 / 17	96 / 636
29	M.o. machinery and equipment	15 / 266	42 / 439	41 / 254	32 / 116	22 / 109	152 / 1184
30	M.o. office machinery and computers	0 / 5	0 / 3	0 / 4	0 / 0	1 / 6	1 / 18
31	M.o. electrical machinery	10 / 95	15 / 141	17 / 77	7 / 40	12 / 28	61 / 381
32	M.o. radio, TV	2 / 24	6 / 42	4 / 35	7 / 19	3 / 32	22 / 152
33	M.o. medical and optical instruments	14 / 110	19 / 106	7 / 46	9 / 17	3 / 19	52 / 298
34	M.o. motor vehicles	3 / 21	5 / 33	2 / 20	4 / 12	15 / 38	29 / 124
35	M.o. other transport equipment	0 / 5	2 / 13	2 / 3	2 / 6	4 / 11	10 / 38
36	M.o. furniture, manufacturing n.e.c.	19 / 134	27 / 164	17 / 69	4 / 21	1 / 7	68 / 395
	Total	289 / 2436	378 / 2466	208 / 1079	111 / 461	87 / 375	1073 / 6817

Notes: Numbers represent the number of firms in estimation sample / original sample.