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Effects of innovation on employment: A dynamic panel analysis

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ABSTRACT

This paper estimates the effect of innovation on employment at 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. We can distinguish between product and process innovations as well as between innovation input and innovation output measures. Using dynamic panel GMM system estimation we find positive effects of innovation on employment. This is true for innovation input as well as for innovation output variables. Innovations show their positive effect on employment with a time lag and process innovations have higher effects than product innovations.

1. Introduction

1.1. The issue

This paper estimates the effect of innovation on employment at the firm level using a dynamic panel approach. The direction of this effect remains unclear in theoretical analyses and thus 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 overall effects on the labor demand of a firm are not clear. Product innovations lead to new products on the market which stimulate 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. This can lead to a reduction in output and thus to a reduction in employment. Especially, 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 production of the old products. This effect is in the opposite direction to the direct effect. Thus, the overall effect of product innovations on employment is 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 improving the productivity of inputs, e. g. labor. So the firm is able to produce the same level of output with less workers. This implies therefore a negative effect of process innovations on employment. But one also has to consider an important indirect effect here. A firm that raises its productivity reduces its production costs and will tend to increase its production. This increase in production level and output allows the firm to hire additional workers. This effect might outweigh the direct effect and therefore it is not possible to draw a definite conclusion about the direction of the effect of process innovations on labor demand.

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

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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 at the firm level. Another strand of literature deals with the same question on the industry or macro level. However, in this study we want to concentrate our analysis on the firm level. A detailed overview of the existing literature is given by Chennells and Van Reenen (2002).

The first studies are, due to data availability, mostly cross-sectional analyses. Entorf and Pohlmeier (1990) and Zimmerman (1991) analyze German micro data. Entorf and Pohlmeier (1990) find a positive effect for product innovations, while process innovations show no significant effects. Zimmerman (1991) concludes that technological progress was important for the employment decrease in 1980, i.e. he finds a negative effect of innovation. But the definition of innovation he uses refers to a question asking explicitly for the implementation of labor-saving technological progress. Blanchflower and Burgess (1998), 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, allowing the authors to analyze growth rates, a methodology which eliminates unobserved firm heterogeneity. Brouwer et al. (1993) use 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 from 1991 for analyzing employment growth from 1986 to 1990. They find positive effects of both process and product innovation with the effect for product innovations being higher.

Recent studies that use the Community Innovation Survey (CIS)–the harmonized European innovation survey–are also analyzing employment growth rates. With this survey comparable innovation data for different countries are available. 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 analysis 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. The results show again positive effects of product innovation on employment growth and demonstrate that displacement and compensation effects of process innovations are present in the manufacturing sector.

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 positive effects of product as well as process innovations on employment. Lachenmaier and Rottmann (2007) use a static panel approach and also find significantly positive 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 and innovation. Rottmann and Ruschinski (1998) use the Ifo Business Survey of the years 1980 to 1992.[2] Using an Anderson–Hsiao dynamic panel approach the authors 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. In addition, his measure of innovation differs from ours, as the SPRU innovation counts refer only to the major, most influencing innovations and do not measure small innovative progress. A similar model is estimated by Piva and Vivarelli (2004, 2005) for Italy using gross innovative investment as innovation measure. Using GMM system estimations they find small but significantly positive employment effects of technological change.

1.3. Contribution

To sum up, most studies find a positive relationship between product innovations and employment whereas the analysis 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. 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 between different levels of importance of innovations. We also test for heterogeneous effects of innovation on employment in different economic sectors, in West and former East Germany, and for different effects of innovation on employment across time.

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. Econometric modeling

2.1. The employment demand equation

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

$$n_{i,t} = \beta_1^{'} X_{i,t} + \gamma_i + \varepsilon_{i,t} \quad \text{with } i = 1, \ldots, N, \text{ and } t = 1, \ldots, T \tag{1}$$

$n_{i,t}$ 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. $\varepsilon_{i,t}$ is an independently distributed error term with $E[\varepsilon_{i,t}] = 0$ for all i and t. γ_i is an unobserved firm-specific time-invariant effect which may be correlated with the variables in X but not with the $\varepsilon_{i,t}$. However, a static estimation equation might lead to some problems. The high costs of hiring and firing are a well-known argument for costly employment adjustment, especially in European economies. If a firm faces these high costs, the actual employment will deviate from the equilibrium level in the short-run. The short-run dynamics compound influences from

[2] The "Ifo Business Survey (Konjunkturtest)" is a survey on business situation and business expectation among German enterprises and is conducted by the "Ifo Institute for Economic Research" in Germany. Its results serve as a data basis for the construction of a leading indicator for the German economy. It contains one question on whether product or process innovations were undertaken in the respective year.

adjustment costs, expectation formation and decision processes. Therefore, a dynamic panel data model is considered that includes unrestricted lag structures in order to model the slow adjustment.[3]

$$c(L)n_{i,t} = \beta^{'}(L)X_{i,t} + \gamma_i + \varepsilon_{i,t}, \tag{2}$$

Here $c(L)$ denotes the corresponding polynomial in the lag operator for $n_{i,t}$.[4] We also include lagged values of the innovation variables to account for a time lag between the implementation of an innovation and its effect on employment. Therefore $\beta(L)$ is a vector of associated polynomials in the lag operator for the vector $X_{i,t}$.

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

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

Our base specification includes contemporaneous values and two lags of employment n, product innovation I^{Pd} and process innovation I^{Pd}. Additionally, we include several control variables. In the 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 the demand situation in the respective industry. In other specifications we use simple dummy variables for the NACE 2-digit industries[5] and years or combinations of dummy and continuous variables.

2.2. Estimation approach

The next question is how to estimate Eq. (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 OLS estimates for the lagged dependent variables are biased upwards. To eliminate the 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. After demeaning the equation, the transformed variables on the right-hand side of Eq. (3) are correlated with the demeaned error term $(\varepsilon_{i,t} - \bar{\varepsilon}_i)$. Especially $(n_{i,t-1} - \bar{n}_{i-1})$, where $\bar{n}_{i,-1} = \frac{1}{(T-1)} \sum_{t=2}^{T} n_{i,t-1}$, is negatively correlated with the demeaned error term. 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 $T \rightarrow \infty$ the within estimator will be consistent for the dynamic panel data model. However, T is typically small in micro panel data sets.[6]

For this reason one uses the first-differenced equation of Eq. (3) to eliminate the firm fixed effect:

$$\begin{aligned} \Delta n_{i,t} = {} & \sum_{j=1}^{2} \beta_j \Delta n_{i,t-j} + \sum_{j=0}^{2} \beta_{3+j} \Delta I^{Pd}_{i,t-j} + \sum_{j=0}^{2} \beta_{6+j} \Delta I^{Pc}_{i,t-j} \\ & + \beta_9 \Delta w_{it} + \beta_{10} \Delta d_{it} + \Delta \varepsilon_{i,t} \text{ and } t = 4, 5, \ldots, T \end{aligned} \tag{4}$$

where $\Delta n_{i,t} = n_{i,t} - n_{i,t-1}, \Delta n_{i,t\text{-}j} = n_{i,t\text{-}j} - n_{i,t\text{-}j-1}$ and all other variables are defined in the same way.

In the following we will explain our estimation strategy. This starts with explaining the handling of the lagged dependent variables. After this, we discuss the other covariates. If we accept–in addition to the assumptions on the error terms discussed after Eq. (1)–the following standard assumption concerning the initial condition $n_{i,1}$ (see e.g. Blundell and Bond, 1998)[7]

$$E(n_{i,l}\varepsilon_{i,t}) = 0 \quad \text{for } i = 1, \ldots, N \text{ and } t = 2, \ldots, T \tag{5}$$

then there are instruments for the lagged differenced dependent variable $(\Delta n_{i,t-1})$ available to avoid the correlation with the error term in Eq. (4). There exist various suggestions for such estimators, which differ in the set of instruments they use. The estimator proposed by Anderson and Hsiao (1982) for an AR(1)-process uses one further lag (either as level $n_{i,t-2}$ or as difference $\Delta n_{i,t-2}$) 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 level values of the lagged differenced dependent variable. Their estimation strategy uses the moment conditions $E(n_{i,t\text{-}s}\Delta\varepsilon_{i,t}) = 0$ for $t = 4,...,T$ and $s \geq 2$. This is why this strategy is also called GMM difference estimation. These instruments are only valid in the case of no autocorrelation of $\varepsilon_{i,t}$. Arellano and Bond (1991) suggested a test for autocorrelation in their model.

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 past values are weak instruments when using the GMM difference estimator. As we will see in the course of this paper the assumption of high persistency is true for the employment variable we use in this paper. Blundell et al. (2002) show with simulations including weakly exogenous covariates that the GMM difference estimator has large finite-sample bias and very low precision. In these cases the GMM difference estimator for the lagged dependent variable is strongly biased downwards, in the same direction as the within estimator (Bond, 2002).

The GMM system estimator extends the model by using moment restrictions of a simultaneous system of first-differenced equations and the equations in levels. In the first-differenced equations one uses the lagged level values of the variables as instruments like in the GMM difference estimator. In the levels equations one uses lagged differences as instruments.[8] This estimation strategy requires additional $T-3$ moment conditions to be valid: $E(\Delta n_{i,t-1}(\varepsilon_{i,t} + \gamma_i)) = 0$ for $t = 4, 5, \ldots, T$.

These moment conditions are fulfilled when the log change of employment is not correlated with the firm-specific effects γ_i and with the epsilon of the next period (i.e. the firm does not have knowledge about future shocks). Blundell and Bond (1998) have shown, that a mean stationarity assumption on the initial condition allows the use of these instruments. These additional moment conditions for the levels equations can be tested given the validity of the moment conditions for the difference equations: Since the moments used in the GMM difference approach are a strict subset of the instruments used in the GMM system estimation, the validity of

[3] See Baltagi (2008) for an introduction to the econometrics of dynamic single equation panel data models.

[4] For stability of the dynamic equation the inverses of all roots of the lag operator polynomial $c(L)$ must be inside the unit circle.

[5] The NACE classification system is the "Classification of Economic Activities in the European Community" and similar to the international ISIC code system ("International Standard Industrial Classification of all Economic Activities"). For details of the classification see Table A2 in the Appendix.

[6] See e.g. Hsiao (2003), ch. 4.

[7] This condition is fulfilled, if the firm does not know future shocks in period one. For n_{i2} there exists an analogous condition.

[8] One can use $\Delta n_{i,t-1}$ as instrument for the lagged dependent variable $n_{i,t-1}$.

the additional instruments can be tested by a Sargan difference test (Blundell and Bond, 1998).

Next, we will discuss the treatment of the innovation variables. The set of moment conditions that will be available depends on what is assumed on the correlation between the innovation variables and the error components. Since we measure employment and innovation both at the firm level, it is very likely that innovation variables are correlated with the firm-specific effect. For the same reason it is not possible to treat the innovation variables as strictly exogenous in the sense that innovations are not correlated with $\varepsilon_{i,t}$ and any earlier or future shocks. If the companies decide simultaneously on their labor demand and their innovation behavior, then the innovation variables are endogenous in the sense that $I_{i,t}^{Pd}$ and $I_{i,t}^{Pc}$ are correlated with $\varepsilon_{i,t}$ and earlier shocks. Thus we would not estimate the causal effect using simple estimation methods. In dynamic panel estimations, however, one can also instrument the potentially endogenous variables. Similar as for the lagged dependent variable, this is done by using the appropriate lags as instruments of the variables. In general, if $x_{i,t}$ is endogenous, $x_{i,t-2}$ and earlier realizations of x_i are available as valid instruments for $\Delta x_{i,t}$ in the first-differenced equation and $\Delta x_{i,t-1}$ and earlier realizations of Δx_i are available as instruments in the level equation for $x_{i,t}$ if $x_{i,t}$ is endogenous.

If we assume that innovation decisions in companies are often based on long-term considerations because of their high costs and of the sometimes irreversible changes coming with innovations, and if we further assume that labor decisions are taken based on rather short-term considerations, then additional moment restrictions can arise. If the company makes its innovation decision at least one period ($t-1$) before the employment decision (t) we can treat the innovation variables as predetermined and get then additional moment conditions if we additionally assume that the firm does not know future shocks (epsilons) when making innovation decisions at time $t-1$. If $x_{i,t}$ is predetermined, we can additionally use $x_{i,t-1}$ as valid instrument in the differenced equation and $\Delta x_{i,t}$ as valid instrument in the level equation.

These differences are valid instruments in the level equation if they are not correlated with the firm-specific effects. Because we do not know a priori about the validity of these additional moment conditions, we use Sargan difference tests to test these assumptions.

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 estimator and the Arellano–Bond estimator, these regression methods give us upper and lower bounds of the range where we can expect the estimation coefficient. As we will show in our results section after the description of the database this is also true for our study.

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. Today the survey is still carried out regularly. For this paper we use data up to the survey of the year 2003, which describes firms' behavior in 2002.[9]

Each year information from on average 1500 respondents is collected. Most questions in the questionnaire are related to the innovation behavior in the preceding year. The discussion on how to measure innovations correctly is still ongoing. In the "Oslo Manual"–an innovation survey manual published by the OECD and Eurostat–the importance of using both innovation input and innovation output measures is stressed (OECD and Eurostat, 2005). The Ifo Innovation Survey offers us to deal with both types of innovation measures: First, we can use questions whether any innovations were introduced and how important they are (innovation output). Second, we can use the innovation expenditure which reflects the input to the innovation process.[10]

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 the preceding year. In addition we can obtain further information on the importance of an innovation: One question indicates whether the implemented innovations required R&D activities. Another question indicates whether patent applications were filed for the innovations. Patent applications are very expensive and so we expect that they are filed only for few important innovations, for which the firms expect high returns.

Our second measure–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 questionnaire's industry classification (NACE 2-digit level). By using these control variables and the additional use of year dummy variables we also try to control for the variation in working hours. We thus control for overall trends and developments, but also for differences in the workers' structure between industries.

Unfortunately, we do not get any information on wages in the firms. However, we include the real hourly wage rate within a 2-digit industry as the best approximation available from the National Statistical Office. From this source we also get data on the Gross Value Added (GVA) in 2-digit industries. This can serve as a proxy for the demand situation 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 31,885 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. Firms only remain in the estimation sample if data of at least six consecutive observations is available. This technique can result in a data set with several intervals for one firm if the firm did not respond in one or more years. In these cases we only consider the

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

[10] 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).

longest period of consecutive answers for one firm. If two series have the same number of observations, we only consider the newest one.

Keeping only the longest series of consecutive observations of firms with at least six consecutive observations and dropping observations with missing values in the variables of interest reduces our estimation sample to 9682 observations from 1073 different firms. That means, on average we can include nine observations per firm. The data cleaning process might raise some concern about the representativeness of our sample. Table A1 in the Appendix A 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 larger mean values in the estimation sample. As can be seen in Table A1 an average firm in our sample has a size of 608 employees. This number is driven heavily by few very large firms, as the median firm in our sample has 129 employees compared to 100 in the original sample. Therefore, we crosscheck all following estimations with a restricted sample excluding extreme outliers. This restricted sample, which excludes the lowest and the largest percentile of firms in terms of employees, shows an average value of 311 employees.

Table A2 in the Appendix A shows the distribution of the firms across 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 for measuring innovation 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. Distinguishing between product and process innovations we see that more firms introduced product innovations (42%) than process innovations (33.7%).[11] Next, we look at questions describing the innovations introduced in more detail: 34.8% of the respondents indicated the introduction of a new product for which R&D was necessary and 21.9% reported a process innovation which required R&D. 19.8% 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 in terms of significance levels later.

We have to reduce our sample when using innvation expenditure 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 5828 observations from 690 different firms. We create two different variables for the innovation expenditure: One is simply indicating whether the firm reported any positive innovation expenditure at all for a certain year, the second refers to real innovation expenses.[12] 47.3% of the respondents reported positive innovation expenditure. The mean of the innovation expenses is about 7 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).

[11] We use a non-exclusive definition of product and process innovation in this paper. We only focus on whether one of the two types of innovation was introduced, where it is not important whether the second type was also introduced. The alternative would be a distinction between non-innovators, product innovators only, process innovators only and innovators which introduced both types.

[12] 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.

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Employment	9682	608	3874	1	99,999
Log employment	9682	4.863	1.547	0	11.513
Innovation	9682	0.513		0	1
Product innovation	9682	0.420		0	1
Process innovation	9682	0.337		0	1
Product innovation (R&D)	9081	0.348		0	1
Process innovation (R&D)	9081	0.219		0	1
Product innovation (patents)	9081	0.198		0	1
Process innovation (patents)	9081	0.025		0	1
Innovation expenditure (dummy)	5828	0.472		0	1
Innovation expenditure (in 1000 €)	5828	7274	94,422	0	2,601,066
Log sectoral gross value added	9682	4.528	0.135	3.301	5.382
Log sectoral real hourly wage rate	9682	2.925	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	49,744
Avg. yearly employment growth	197	0.025	0.137	−0.349	0.827
Occasional innovators					
Employment	685	364	1524	2	37,033
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

We find significant differences for these three groups. First it seems that permanent innovators are mainly large firms. The mean firm size of permanent innovators is 1326, going down to 364 for occasional innovators and 125 for non-innovators. Second, it is also interesting to look at the comparison of the average yearly growth rate of employment during the observation period: Permanent innovators grow with an average yearly growth rate of 2.5% whereas occasional innovators on average almost stay at the same size and non-innovators shrink with an average yearly growth rate of −2.3%. This can be interpreted as a first descriptive evidence for a positive relationship between innovations and employment at the firm level.

4. Results

4.1. Basic results

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

The number of observations in Table 3 decreases compared to Table 1 because of the underlying AR(2) process. As a consequence two previous time periods are needed for building lags in the dynamic estimation model. As one can see in Table 3, the coefficients of the lagged dependent variables behave exactly as expected and described in Section 2.2. The estimators of the lagged dependent variables add to a sum of 0.982 for the OLS model in Specification (1), 0.383 in the fixed effects model (within estimator) of Specification (2), 0.475 in the GMM difference model in Specification (3) and 0.838 in the GMM system estimation in Specification (4).[13] This confirms the expected

[13] The dynamic panel estimations were estimated using the Stata command xtabond2, written by David Roodman (Roodman 2006).

Table 3
AR(2) process of employment.

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

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

directions of the bias for the estimations of the coefficients of the lagged dependent variables. Since employment is a near unit root process, it is well-known that the estimates in the OLS model are biased upwards and in the simple fixed effects approach (2) are biased downwards (e.g. Baltagi, 2008). The estimates of the GMM difference model (3) are close to the estimates of the within estimator (2). Using Monte Carlo experiments Blundell et al. (2002) and Blundell and Bond (1998, 2000) show that the coefficients for the lagged dependent variable are strongly biased downwards in the GMM difference model in the case of near unit root processes. The estimates in the GMM system estimation lie between the upper bound of the OLS model and the lower bound of the fixed effects and the GMM difference model. Thus we use the GMM system estimator in our following estimations. However, in each specification we test for the validity of the additional moment restrictions in the GMM system model compared to the GMM difference model.

Table 4 shows the results of our specifications using the simple product and process innovation dummies as our innovation measures. Specifications (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 shocks that are common for all firms. Specification (7) includes year dummies and industry dummies. The choice of the specification only affects the other control variables and has no relevant impact on the estimated effects of the innovation variables. In Specification (5) the sector variables for real hourly wage rate and Gross Value Added (GVA) both show significant effects as expected. The wage rate has a significantly negative effect on employment whereas the GVA — as a proxy for 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 specifications with year dummies only as the sector effect is captured well by the GVA (Specification (6)).

In Specifications (6) and (7) 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.[14] 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 in any of the specifications.[15]

[14] 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.

[15] 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.

Table 4
GMM system estimation results.

	(5)	(6)	(7)
Lag employment	0.744	0.743	0.679
	*(0.088)****	*(0.080)****	*(0.082)****
2nd lag employment	0.130	0.139	0.155
	*(0.061)***	*(0.055)***	*(0.056)****
Product innovation	−0.004	−0.001	−0.008
	(0.046)	*(0.039)*	*(0.041)*
Lag product innovation	0.012	0.014	0.017
	(0.014)	*(0.013)*	*(0.013)*
2nd lag product innovation	0.009	0.015	0.017
	(0.010)	*(0.008)**	*(0.008)***
Process innovation	0.018	0.034	0.040
	(0.032)	*(0.033)*	*(0.037)*
Lag process innovation	0.025	0.023	0.023
	*(0.010)***	*(0.009)***	*(0.010)***
2nd lag process innovation	0.015	0.016	0.017
	*(0.008)***	*(0.007)***	*(0.007)***
Real hourly wage rate	−0.190	−0.126	−0.020
	*(0.051)****	*(0.083)*	*(0.110)*
Gross value added	0.050	0.047	−0.064
	*(0.015)****	*(0.015)****	*(0.069)*
Year dummies	–	incl.	incl.
Sector dummies	–	–	incl.
Constant	1.290	0.949	1.165
	*(0.327)****	*(0.462)***	*(0.510)***
Observations	7536	7536	7536
Number of firms	1073	1073	1073
Sargan value	*243*	*192*	*191*
(degrees of freedom)	*(205)*	*(205)*	*(205)*
Sargan p-value	(0.035)	(0.734)	(0.754)
AR(1)	−2.780***	−2.911***	−2.779***
AR1 p-value	(0.005)	(0.004)	(0.005)
AR(2)	−0.640	−0.863	−1.199
AR(2) p-value	(0.522)	(0.388)	(0.230)

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

The coefficients of the lagged dependent variables confirm the importance of including these variables. In all three specifications the effect is quite similar. In Specification (6), our preferred model, we find a significant effect of 0.743 for the first lag and a significant effect of 0.139 for the second lag. A test for the sum to be one is rejected, which supports the stability of the model. The size of these coefficients is very stable in all our following regressions. They are also very similar to the results of other studies. Piva and Vivarelli (2005) use only one lag of the dependent variable and find a coefficient of about 0.86, in van Reenen's (1997) study the sum of two lags varies between 0.4 and 0.8.

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 (see Section 2.2). This distinction defines which instruments are valid.[16] 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 specifications we will treat innovation as endogenous.

Next we will turn to the analysis of the effects of innovation. 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

[16] 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 equation in period t and differences from period two up to period t as instruments for the level equation in period t. 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 in period t; cf. Section 2).

innovation and a positive effect would be expected according to the direct effect from theory (cf. Section 1). Partly, this might be due to the definition of innovation in the Ifo Innovation Survey that includes also very small innovations. We will test in later specifications how the more important innovations affect employment. However, the results lead to the assumption that product innovations take some time to show their effect on employment. Process innovations, however, show a clearly positive effect on employment. Again the lagged variables show significantly positive effects, but as for process innovations these are the first and the second lag. This result supports the hypothesis that the indirect effects of process innovations are present and firms pass on the productivity gains to lower prices and thus can 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, 1998 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, 2007). These interesting results can be transferred to policy implications. This at least raises some doubts on the pure concentration on product innovations and suggests that process innovations should also be considered when talking about research subsidies. However, with our analysis we only address effects within the firm and not effects on sectors or the whole economy.

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

We also conduct more robustness tests by using different lag structures as instruments. In our standard specifications we use three lags as instruments in the differenced equation, i.e. for an endogenous explanatory variable in the first-differenced equation (ΔX_t), we use $X_{i,t-2}$, $X_{i,t-3}$ and $X_{i,t-4}$. As tests for robustness we estimate specifications, in which we use two to five lags und a specification where we use all available valid lags as instruments. In specifications with two to five lags we find no qualitative and only minor quantitative changes in the coefficients. In specifications using all available valid lags as instruments, the coefficient of the second lag of product innovations sometimes gets insignificant, which is due to an increase in the standard error whereas the coefficient does hardly change. The significantly positive effect of process innovations remains.[17]

In Table 5 we check for potential variation in the effects of innovation on employment according to some further distinctions that our data set allow. First, in Specification (8) we reduced our estimation model by dropping contemporary innovation variables as they did not prove to be significant in any specification so far. As expected, the coefficients are stable and very similar to Specification (6). Thus, we use this model without contemporaneous innovation variables to include further interaction terms to check for some effect heterogeneity of innovation on employment.

In Specification (9) we distinguish between innovations in high-tech sectors and in standard sectors. The classification builds on a distinction used in Felix (2006). Sectors classified as high-tech sectors are NACE categories 30, 32 and 33, i.e. "Manufacture of office machinery and computers", "Manufacture of radio, television and communication equipment and apparatus" and "Manufacture of medical, precision and optical instruments, watches and clocks". However, estimation results do not suggest any significant heterogeneity in the effects that innovation has on employment.[18] Standard errors of the estimated coefficients of the interaction dummies are relatively high in comparison to the standard errors of the parameters of the innovation variables. This suggests that there might be not enough data for high-tech firms to estimate statistically significant effects and reject homegeneity. Specification (10) tests for effect heterogeneity between former West and East Germany. As those two former parts of Germany still show some economic differences after the reunification we could expect innovations to show different effects on employment. But again results do not suggest the presence of heterogeneity in the effects.

As our estimation sample includes a long period of observations we also test for differences in the effect of innovations over time. For this reason, we use interaction terms with a linear time trend for the innovation variables. The results are shown in Specification A3-2 in

Table 5
Effect heterogeneity.

	(8)	(9)	(10)
Lag employment	0.746	0.762	0.754
	*(0.079)******	*(0.063)******	*(0.072)******
2nd lag employment	0.143	0.144	0.141
	*(0.054)******	*(0.049)******	*(0.051)******
Lag product innovation	0.016	0.018	0.017
	(0.010)	*(0.010)**	*(0.011)*
2nd lag product innovation	0.014	0.015	0.020
	*(0.008)**	*(0.009)*	*(0.008)****
Lag process innovation	0.024	0.023	0.028
	*(0.009)******	*(0.009)****	*(0.010)******
2nd lag process innovation	0.016	0.016	0.018
	*(0.007)****	*(0.007)****	*(0.007)******
Lag product innovation (high-tech)	–	−0.059	–
		(0.056)	
2nd lag product innovation (high-tech)	–	−0.015	–
		(0.043)	
Lag process innovation (high-tech)	–	0.036	–
		(0.062)	
2nd lag process innovation (high-tech)	–	0.020	–
		(0.045)	
Lag product innovation (East)	–	–	−0.038
			(0.052)
2nd lag product innovation (East)	–	–	−0.102
			(0.074)
Lag process innovation (East)	–	–	0.010
			(0.062)
2nd lag process innovation (East)	–	–	0.027
			(0.052)
Real hourly wage rate	−0.119	−0.038	−0.081
	(0.081)	*(0.065)*	*(0.079)*
Gross value added	0.047	0.039	0.046
	*(0.015)******	*(0.012)******	*(0.015)******
Year dummies	incl.	incl.	incl.
Constant	0.899	0.462	0.698
	*(0.447)****	*(0.331)*	*(0.410)**
Observations	7536	7536	7536
Number of firms	1073	1073	1073
Sargan value	*195*	*250*	*286*
(degrees of freedom)	*(207)*	*(347)*	*(275)*
Sargan *p*-value	(0.720)	(1.000)	(0.305)
AR(1)	−2.92***	−3.03***	−3.00***
AR1 *p*-value	(0.004)	(0.002)	(0.003)
AR(2)	−0.89	−0.92	−0.89
AR(2) *p*-value	(0.371)	(0.360)	(0.375)

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

[17] Detailed results are not shown, but are available from the authors upon request.

[18] We also tested a broader definition of high-tech sectors that includes NACE categories 29 to 35 according to a strategy used in Lachenmaier and Wößmann (2006). The results are very similar to the narrower definition of high-tech sectors and can be found in Table A3 in Specification A3-1 in the Appendix A.

Table A3 in the Appendix A. They suggest that it is not necessary to revise the previous conclusions. Only the interaction term of product innovations (second lag) is significant and shows a negative sign, but the second lag of product innovations shows a highly significant positive effect. Thus, product innovations had a higher positive effect at the beginning of our estimation period than at the end. If we calculate the overall effects at the end of the observation period, the impact of product innovations on employment almost vanishes.

4.2. Results using different innovation measures

In Table 6 we use different innovation output measures. In Specification (11) we replace the simple innovation variables by those for which firms responded that R&D was necessary. The results for both types of innovation are quite similar to those of Specification (6) with the simple innovation indicators. Again, for product innovations only the second lag shows a significant effect, whereas for process innovations the first and the second lag show significant effects. Also, as for the size of the effects, results are very similar to the estimates before. Joint significance tests 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.

Table 6
Further GMM system estimation results.

	(11)	(12)
Lag employment	0.780 *(0.072)******	0.670 *(0.067)******
2nd lag employment	0.121 *(0.050)****	0.185 *(0.045)******
Product innovation (R&D)	−0.004 *(0.046)*	–
Lag product innovation (R&D)	0.012 *(0.018)*	–
2nd lag product innovation (R&D)	0.022 *(0.013)**	–
Process innovation (R&D)	−0.016 *(0.044)*	–
Lag process innovation (R&D)	0.033 *(0.013)****	–
2nd lag process innovation (R&D)	0.029 *(0.010)******	–
Product innovation (Patent)	–	0.210 *(0.057)******
Lag product innovation (patent)	–	0.007 *(0.020)*
2nd lag product innovation (patent)	–	0.036 *(0.014)******
Process innovation (patent)	–	0.100 *(0.127)*
Lag process innovation (patent)	–	0.051 *(0.054)*
2nd lag process innovation (patent)	–	0.099 *(0.076)*
Real hourly wage rate	−0.029 *(0.075)*	−0.039 *(0.114)*
Gross value added	0.036 *(0.012)******	0.037 *(0.014)******
Year dummies	incl.	incl.
Constant	0.430 *(0.410)*	0.672 *(0.576)*
Observations	6963	6963
Number of firms	1059	1059
Sargan value (degrees of freedom)	192 (205)	183 (205)
Sargan *p*-value	(0.741)	(0.866)
AR(1)	−2.933***	−2.942***
AR1 *p*-value	(0.003)	(0.003)
AR(2)	−0.251	−1.625
AR(2) *p*-value	(0.802)	(0.104)

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

Table 7
GMM system results using innovation input variables.

	(13)	(14)
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 value (degrees of freedom)	140 (134)	165 (152)
Sargan *p*-value	(0.336)	(0.226)
AR(1)	−4.857***	−5.325***
AR1 *p*-value	(0.000)	(0.000)
AR(2)	−1.463	−1.189
AR(2) *p*-value	(0.144)	(0.235)

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

Specification (12) uses those innovations which went along with patent applications. We have to keep in mind that the number of firms with process innovations and at the same time 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 tests in this specification show no significance for process innovations. Product innovations show a joint significant effect at the 1% level. Test statistics support the validity of our results in all specifications.

In Table 7 we replace the innovation output variables used so far by variables which measure the input into the innovation process. Results are shown for two different measures of innovation input. Unfortunately, not all firms respond always to the question relating to innovation expenditure. So, our sample is reduced 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 present two different specifications. In Specification (13) we replaced the original innovation expenditure by one plus the original value. This leads to a value of zero for non-innovators after taking the logarithm. This method is sometimes used in such cases, but does not distinguish anymore between innovators and non-innovators by replacing zero innovation expenditure with low positive values.[19]

[19] We also tested other values than 1. 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.

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 the market. In contrast to Specification (13) we concentrate on the distinction between firms with and without innovation expenditure in Specification (14). In this specification 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.

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. An exception of this pattern are product innovations for which patent applications were filed, which show a very high and significantly positive effect. As for the input variables, the estimations also lead to significantly positive effects. Innovation output variables usually show their effects faster than the innovation input variable, which is innovation expenditure.

5. Conclusions

The effect of innovation on employment remains unclear in theoretical contributions. This calls for answering this question empirically. With an increasing data availability it is possible to estimate the effects at the firm level—the level at 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 output is measured by information about innovations introduced or implemented. Innovation input is measured by innovation expenditure. As for innovation output, we can distinguish between product and process innovations, as proposed by theoretical contributions. In addition, the innovation output indicators can further be divided into several categories reflecting the importance of innovations. We test for the robustness of our results in different economic sectors, geographical regions in Germany and over time.

To control for unobserved firm heterogeneity, endogeneity of innovation with respect to employment and dynamics we employ dynamic panel analyses. The effect of the lagged dependent variable is almost stable across all specifications. The effects of innovation on employment 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 a 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. In addition, we use our comprehensive data set to test for heterogeneous effects between economic sectors, geographical regions in Germany and over time. Results suggest that effects do not differ between sectors or regions, but that product innovations have a higher positive effect at the beginning of our estimation period than at the end.

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Appendix A

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	9682	608	45	129	350
Innovation	31,420	0.494				9682	0.513			
Product innovation	31,420	0.403				9682	0.420			
Process innovation	31,420	0.315				9682	0.337			
Product innovation (R&D)	30,995	0.329				9081	0.348			
Process innovation (R&D)	30,488	0.195				9081	0.219			
Product innovation (patents)	30,995	0.190				9081	0.198			
Process innovation (patents)	30,488	0.023				9081	0.025			
Innovation expenditure (dummy)	24,978	0.512				5828	0.472			
Innovation expenditure	24,978	3343	0	11.3	466	5828	7274	0	0	423

Notes: p25: 25th percentile, p75: 75th percentile.

Table A2
Distribution of firms in NACE 2digit sector and size classes.

NACE 2digit classification		−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

Table A2 (*continued*)

NACE 2digit classification		−49 employees	50–199 employees	200–499 employees	500–999 employees	1000+ employees	Total
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.

Table A3
Additional estimations.

	(A3-1)	(A3-2)
Lag employment	0.749 *(0.054)******	0.817 *(0.049)******
2nd lag employment	0.152 *(0.042)******	0.128 *(0.046)******
Lag product innovation	0.015 *(0.012)*	0.011 *(0.016)*
2nd lag product innovation	0.005 *(0.010)*	0.059 *(0.018)******
Lag process innovation	0.019 *(0.010)**	0.037 *(0.018)****
2nd lag process innovation	0.014 *(0.008)**	0.026 *(0.015)**
Lag product innovation (high-tech)	−0.022 *(0.028)*	–
2nd lag product innovation (high-tech)	0.023 *(0.034)*	–
Lag process innovation (high-tech)	0.013 *(0.022)*	–
2nd lag process innovation (high-tech)	0.007 *(0.019)*	–
Lag product innovation time trend	–	0.001 *(0.001)*
2nd lag product innovation time trend	–	−0.004 *(0.002)****
Lag process innovation time trend	–	−0.000 *(0.002)*
2nd lag process innovation time trend	–	−0.000 *(0.001)*
Real hourly wage rate	−0.070 *(0.070)*	−0.119 *(0.081)*
Gross value added	0.040 *(0.016)****	0.047 *(0.015)******
Year dummies	incl.	incl.
Constant	0.639 *(0.362)**	
Observations	7536	*7536*
Number of firms	1073	1073
Sargan value (degrees of freedom)	*324* *(347)*	*242* *(241)*
Sargan *p*-value	(0.812)	(0.473)
AR(1)	−3.27***	−3.38***
AR1 *p*-value	(0.001)	(0.001)
AR(2)	−1.25	−0.66
AR2 *p*-value	(0.212)	(0.511)

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

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