The Labour Demand and the Innovation Behaviour of Firms

An Empirical Investigation for West German Manufacturing Firms*

by

Horst Rottmann
Monika Ruschinski

Abstract

From a theoretical point of view the introduction of process and product innovations has contrary impacts on labour demand even at the level of the innovating firm. We present an empirical study of the relationship between labour demand and innovation behaviour using the Ifo Business Panel for the West German manufacturing sector in the years 1980-1992. A dynamic labour demand function is estimated by the method of instrumental variables. Our main findings can be summarized as follows: The labour demand at the firm level is mainly affected by wages, user costs of capital and the demand side. The impact of product innovations on employment is significantly positive. Finally, we find no empirical evidence for the often-quoted statement that the introduction of process innovations destroys jobs in the enterprise.

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1. Introduction

The effects of innovation on employment are not straightforward. Even at the firm level, there are contrary impacts of firm-specific innovations on labour demand.[1] The theoretical literature generally distinguishes between process and product innovation.[2] Process innovation is often connected with rationalisation and new work organisation which therefore can destroy jobs, whereas product innovation is related to the creation of new job opportunities. An earlier investigation for West German manufacturing firms gives empirical support for these direct effects on the firms' conditional labour demand, which is derived by a cost-minimisation approach.[3]

The analysis of the relation between innovation and labour demand is certainly more complex than is suggested by the cost-minimisation approach. The individual firm does not take output as given, but the output decision process is connected with the firm's innovation behaviour. If, for example, innovations increase the quality of goods or reduce the input requirements, the innovative firm should be more competitive and could increase its output. In this case, the change of labour demand does not depend only on the direct effects of the product and/or process innovation on the production process but also on the size of the indirect output effect of innovations. On the other hand, the resulting output effect is not unambiguous since product innovations could also reduce competition if they influence the market structure via product differentiation. This could lead to higher prices and to less output increases and employment changes than expected. The impacts of innovations on labour demand can differ significantly

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[1] There are only few microeconometric studies of labour demand in connection with technological progress for Germany. See for example Zimmermann (1989), Zimmermann (1991), Konig/Buscher/Licht (1995), Smolny/Schneeweis (1996), Smolny (1996), and Rottmann/Ruschinski (1997).

[2] See Katsoulacos (1986) and Stoneman (1983). Endogeneous growth models also separate product from process innovation. See for example Romer (1990), Grossman/Helpman (1991), Aghion/Howitt (1992) and Barro/Sala-I-Martin (1995).

[3] See Rottmann/Ruschinski (1997). This paper shows empirically that process innovation is 'labour saving' because it increases labour productivity. Product innovation has 'job creating' effects as the production of new or better products needs more employees.

depending on the additional indirect effects on the produced output, which is related to the prevailing market structure and to the price elasticity of product demand.[4]

There are only few empirical studies of labour demand in connection with technological progress for Germany at the firm level (see for example Zimmermann (1989), Zimmermann (1991), König/Buscher/Licht (1995), Smolny/Schneeweis (1996) and Smolny (1996))[5]. These studies are partly - due to the underlying data - limited to cross-section analysis; partly they are based on pooled data, but the heterogeneity of enterprises is not considered. If the individual effects are correlated with the innovation activities of the companies, the impact of technical progress on the employment will be estimated biasedly (Rottmann 1995, pp. 86ff.). Due to the insufficient data bases, the factor prices are not included in some of the above mentioned studies.

The literature contains a variety of results. Zimmermann (1991) finds a negative impact of technical progress on employment by using business survey data to evaluate the determinants of labour demand (i.e. demand, labour costs, technical progress). This may be partially due to the wording of the question (firms were asked whether 'labour-saving technical progress' had an influence on their employment plans). König/Buscher/Licht (1995), on the other hand, find a positive effect of process innovation on employment, which is even stronger than the effect of product innovation. This study, which is based on a cost-minimisation approach, uses a cross-section survey with dummy variables concerning product and process innovation data. In the economic specification of the study, the levels of product and process quality influence employment. In the econometric specification, however, the authors use the dummy variables for product and process innovations as indicators for the corresponding levels. But innovation would be better interpreted as an indicator for change than as an indicator for a level of product and process quality. Furthermore, individual effects cannot be considered. Leo/Steiner (1994) analyse the impact of innovation on employment for the period 1990-1992 based on cross-section information from the Austrian Technology and Innovation Survey (TIS). They find

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[4] An empirical analysis by Smolny (1996) supports the hypothesis that product innovations increase the market share of the firms and reduce the price elasticity of demand.

[5] In some cases, these studies are also based on the cost-minimisation approach.

some evidence that product innovation tends to have a positive impact and process innovation has no significant negative impact on employment.

In this paper we present an empirical study which is based on the Ifo Business Survey Panel for the years 1980-1992. This panel consists of observations for 2405 firms and contains qualitative data for both product and process innovation. This data source provides a rich environment for modern estimation techniques which allows for business heterogeneity. We concentrate on a model with endogenous output, derived in a monopolistic competition framework, and estimate a dynamic unconditional labour demand function with lagged dependent and independent variables. As in dynamic panel models with heterogeneity, the lagged regressor is correlated with the disturbance; an OLS as well as a within-estimator or random-effects GLS estimator would be inconsistent. Therefore, to avoid this correlation problem, we use the Anderson-Hsiao estimation method, which uses first differences and instrumental variables.[6]

Section 2 of the paper explains the theoretical framework and Section 3 the data base. In Section 4 the estimation method and the results are represented.

2. Theoretical framework

We consider a monopolistically competitive firm that maximises profits in a two-stage decision process. At the first stage, the firm determines its innovation activities. The firm invests in R&D in order to reduce costs and/or to increase consumer demand.[7] A firm-specific improvement in product and process quality or the development of a new product, given constant qualities and product groups of the competitors, increases the firm's market share, but it could also lead to higher monopolistic power and mark-up pricing. Thus, the innovation behaviour of the firm can have effects on the market shares and the price elasticity of product demand. At the second stage of the decision process, given the firm's product and process quality and the market structure, the firm decides on the profit maximising output level, price level and factor demands.

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[6] See Anderson/Hsiao (1981, 1982) and Hsiao (1986), ch. 4.

[7] See Levin/Reiss (1988).

We consider only the second stage of the dynamic monopolistic competition model. Neither the actual number of firms in short-term equilibrium is explicitly derived nor a special functional form of the product demand $x_i(t)$ is supposed. To simplify matters, the price-setting firm i faces the following negatively sloped demand function for its product at time t:

$$x_i(t) = x_i(p_i(t), P_{-i}(t), q_i(t), Q_{-i}(t), Z_i(t)), \tag{1}$$

with $x_{i1} < 0, x_{i2} > 0, x_{i3} > 0, x_{i4} < 0$.

$p_i(t)$ denotes the firm's product price, $P_{-i}(t)$ is the vector of prices of competitors; analogously, $q_i(t)$ stands for the own product quality, and $Q_{-i}(t)$ is the vector of qualities of competitive products. $Z_i(t)$ incorporates other factors which are exogenous to the firm in t as demand trends or the firm-specific goodwill. x_{ij} with j=1,...,4 denotes the familiar partial derivatives of the demand function.

The individual firm's cost function reflects the production situation, which is affected by technology and product quality:

$$c_i(t) = c_i(x_i(t), te_i(t), q_i(t), w_i(t), uc_i(t)), \tag{2}$$

with $c_{i1} > 0, c_{i2} < 0, c_{i3} > 0, c_{i4} > 0, c_{i5} > 0$.

$te_i(t)$ and $q_i(t)$ denote the firm's process and product quality, respectively; $w_i(t)$ and $uc_i(t)$ are the factor prices for labour and capital, and c_{ij} with j=1,...,5 represents the partial derivative. We assume that better technology increases the factor productivity and therefore reduces the total production costs, whereas a higher product quality requires more factor inputs which increase the production costs. As usual, higher output and factor prices also raise costs.

Profit maximisation in t leads to the following first order condition:[8]

$$(1 + 1/\eta_i)p_i(\cdot) - c_{i1}(\cdot) = 0 \tag{3}$$

[8] See Franz (1996), ch. 4 and Katsoulacos (1991).

where η_i denotes the price elasticity of product demand with $|\eta_i| > 1$ and c_{i1} represents the marginal costs of output. The optimal output and price level are determined by equations (1) and (3) and then due to the cost function (Sherpard's Lemma) the optimal factor demands can be calculated. The unconditional labour demand of firm i, l_i, is given by:

$$l_i(t) = l_i(te_i(t), q_i(t), Q_{-i}(t), P_{-i}(t), w_i(t), uc_i(t), Z_i(t)), \qquad (4)$$

with $l_{i1} = ?, l_{i2} = ?, l_{i3} < 0, l_{i4} > 0, l_{i5} < 0, l_{i6} < 0$.

We assume that the change in quality and technology is determined by the introduction of product and process innovations. Under these assumptions, the effects of product and process innovation on the firm's labour demand are unclear. In the case of process innovations, there are rationalisation effects on the production side and competitive price advantages on the product market. The labour demand increases if the output growth is sufficient to offset the labour saving effects of process innovation. Product innovation increases the production costs but perhaps reduces the competition so that mark-up may be higher. Moreover, product innovations enable the firms to gain higher market shares. The output effect, however, depends on the price elasticity of demand.

Improvements in the quality of products of other firms weaken the competitive position of the own firm. Therefore, the effects on production and employment will be negative. Price increases of competitors, however, result in price advantages of the own firm, which lead to higher output and employment. An increase in the wage rate raises the marginal costs and decreases the unconditional labour demand. l_{i6} will be negative if the marginal product of labour is a positive function of the capital input.

3. Data base

The data base for the empirical investigation consists of observations of West German manufacturing firms over the period 1980-1992. This panel data set combines the responses of the Ifo

Business Survey, the Ifo Investment Survey and the Ifo Innovation Survey.[9] In the stage of linking together the surveys, those enterprises were selected which participated at least once in all three surveys in the investigated period. The questionnaires of the Business Survey and of the Innovation Survey are related to a special product or product group and not, like the questionnaire of the investment survey, to an enterprise. But for most of the firms the product level corresponds with the whole firm. The thus constructed panel data set consists of 2405 product groups of 1982 enterprises of the West German manufacturing sector. The number of the product groups is not identical with the number of the selected enterprises because the data set includes 310 enterprises with more than one product. It should also be mentioned that the panel data set is not entirely representative for the whole manufacturing sector as large firms are oversampled. This is not a problem as long as the results for small and large firms do not differ significantly.

Most of the data from the Ifo Business Survey are qualitative such as the \`yes´ or \`no´ answers to the questions on ‘completed product innovation’ and on ‘completed process innovation’. These dummy variables signify that a product group has set up at least one product or one process innovation in the corresponding year. From the Investment Survey the quantitative data on employment are used. We know which product group belongs to which enterprise; therefore the data of the Business Surveys can be aggregated at the firm level for the enterprises with more than one product. In addition, we use statistical publications for wage rates, user costs of capital and demand indicators.[10] These additional data are connected on sectoral level via the two-digit SYPRO classification.

A serious problem is the possible sample selection bias when dealing with survey data.[11] For instance, the likelihood of the questions on innovation being answered, could be higher for successful innovators than for non-innovators. However, the response rate for these questions is nearly 90% in this sample. Another source of endogenous sample selection for the Ifo firm

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[9] For a detailed data description, see Schneeweis/Smolny (1996). The different surveys are described in more detail in Oppenländer/Poser (1989).

[10] We used information about the number of employees, the effective yearly working time per employee, and the payrolls in the sectors supplied by *DIW* (1995) to calculate the sectoral wage rates. The user costs of capital are taken from Gerstenberger/Heinze/Hummel/Vogler-Ludwig (1989). Sectoral demand indicators like added value or sectoral price indices are collected by the Statistisches Bundesamt (1994).

[11] On this score, see the data description of Smolny (1996).

panel is attrition. A rather large number of firms left the panel during the observation period. Of 2156 firms in 1980, 548 firms left the panel, while 243 firms entered it. Therefore, for the year 1992, observations of 1851 firms are available. Attrition is usually not a random process. It is reasonable to assume that some exits out of the panel are also exits out of the market. Probably there is an endogeneity of firms' exiting and, therefore, a sample selection bias may exist. One way of dealing with endogenous attrition is to estimate the economic model with a sample selection correction factor. However, an inadequate specification of the selection equation leads also to biased estimations of the parameters.[12] As there is not enough information about the exits, we estimate without a sample selection correction, but we use an unbalanced panel design, i.e. the firms do not answer the questionnaire annually.[13] This unbalanced panel data set covers only 9 years and records 6405 observations because of the time lags.

The sample[14] shows the innovation activities of the participants. In 33% of the observations neither product nor process innovations were introduced. In 12% of the observations only product innovations were carried out, while in 10% only process innovations were realized. 45% show both product and process innovations. The sample includes a comparatively large proportion of participants that introduced no innovations at all in the corresponding year. Furthermore, in more than 20% of the observations only one of the two types of innovation was carried out. These proportions correspond with results of other panel studies.[15]

4. Empirical specification and estimation results

The high cost of hiring and firing is a well-known argument for costly employment adjustment especially in the European economies. If this is the case, the actual employment will deviate from the equilibrium level in the short run. Therefore, a dynamic single equation panel data model[16] is considered that includes unrestricted lag structures in order to model the sluggish

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[12] See Greene (1993), ch. 22.

[13] The use of an unbalanced panel design can lessen the impact of self selection of firms in the sample. See e.g. Arellano/Bond (1991), p. 281.

[14] This sample with 6405 observations is also the basis for the econometric estimation.

[15] König/Buscher/Licht (1995) use for their study the Mannheim Firm Panel of the Centre for European Economic Research (ZEW), which contains similar proportions of innovating firms.

[16] See Baltagi (1995) for a introduction of the econometrics of dynamic single equation panel data models.

adjustment.[17] The short-run dynamics compound influences from adjustment costs, expectations formation and decision processes. We use a log-linear approximation of the demand function derived from our model in equation (4) with a first-order autoregressive term and additional lagged explanatory variables:

$$\ln l_{i,t} = \alpha \ln l_{i,t-1} + \beta'(L) \ln X_{i,t} + \gamma_i + \varepsilon_{i,t}, \qquad |\alpha| < 1, \qquad (4')$$

$i = 1,...,N$, and $t = 1,...,T$.

Here $\ln l_{i,t}$ ($\ln l_{i,t-1}$) is the logarithm of employment in company i at time t (t-1). $X_{i,t}$ contains a set of explanatory variables and $\beta(L)$ is a vector of associated polynomials in the lag operator. The specification also contains a permanent but unobservable firm-specific effect γ_i and an error term $\varepsilon_{i,t}$ with $\varepsilon_{i,t} \sim iid(0, \sigma_\varepsilon^2)$. Note that the autoregressive term and the firm-specific effect are necessarily correlated, and therefore, OLS is inconsistent. Also the within-estimator (often called fixed-effects estimator), which wipes out the γ_i, is inconsistent, because ($l_{i,t-1}$- $\bar{l}_{i,-1}$) where $\bar{l}_{i,-1} = \sum_{t=2}^{T} l_{i,t-1} / (T-1)$ will still be correlated with ($\varepsilon_{i,t} - \bar{\varepsilon}_i$), even if the $\varepsilon_{i,t}$ are not serially correlated. Only if $T \rightarrow \infty$, will the within-estimator of α and β be consistent for the dynamic panel data model, however, T is small for typical panels.[18] The random-effects GLS estimator, which is a weighted average of the within- and between-estimators, is inconsistent for the same reasons.

A simple estimation method for this kind of panel data model was first proposed by Anderson/Hsiao (1981, 1982). The permanent firm-specific effects are wiped out by first difference transformation:

$$\Delta l_{i,t} = \alpha \Delta l_{i,t-1} + \beta'(L) \Delta X_{i,t} + \vartheta_{i,t}, \qquad t = 2,...,T, \qquad (5)$$

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[17] Note that our theoretical model is more static than dynamic. We do not use an Euler equation approach with adjustment costs of the standard additively-separable quadratic form. Therefore, the lag structure of our estimation model is unrestricted. See e.g. Konig/Laisney/Lechner/Pohlmeier (1992) who model the dynamics of process innovations with an Euler equation approach.

with $\Delta l_{i,t} = \ln l_{i,t} - \ln l_{i,t-1}$, etc. and $\vartheta_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$.

OLS is again inconsistent, because $\Delta l_{i,t-1}$ is correlated with the disturbance $\vartheta_{i,t}$. Anderson and Hsiao suggested a consistent instrumental variable estimation with $z_{i,t} = \left[\ln l_{i,t-2}, \Delta X_{i,t}\right]$ or $\tilde{z}_{i,t} = \left[\Delta l_{i,t-2}, \Delta X_{i,t}\right]$ as instruments. These instruments will not be correlated with $\vartheta_{i,t}$ if $\varepsilon_{i,t}$ itself is not serially correlated. This instrumental variable estimation method leads also in the case of a correlation between γ_i and $X_{i,t}$ to consistent but not necessarily efficient estimates of the parameters.[19] Arellano/Bond (1991) have linked this approach with the general method of moments according to Hansen (1982) and White (1982). The efficiency of this estimation method is higher since it makes use of all the available moment conditions.[20] To keep programming efforts for an unbalanced panel design in reasonable limits, an easier estimation method is used instead of the general method of moments-approach.[21] Since our survey data set is highly incomplete, with missing values in the middle of a firm's time series for example, we use the practicable Anderson/Hsiao instrumental variable estimation method.

The panel data contains no information about the level or the growth rate of product and/or process quality, but it contains information about a qualitative change of product and/or process quality (Δq_t, Δte_t). We use dummy variables for reporting successful product and process innovations. The measure of the change of product quality of competitive firms (ΔQ_t) is also based on these qualitative answers of the Ifo questionnaire. It is calculated for each year as the number of competitive product innovators in relation to all competitors which are firms of the relevant two-digit sector. The changes of the user costs of capital and of the wage rates (Δuc_t, Δw_t) are calculated on the sectoral level, such as the changes of added value (ΔY_t) and prices (ΔP_t). For modelling business expectations, we make use of a qualitative variable of the Ifo Business Survey that reports the expected development of the product market for the following five years (BE). The variable is scaled from 1 (the product market will grow markedly) to 5 (the

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[18] See Hsiao (1986), ch. 4.

[19] A priori, it is possible that the firm specific effects are correlated with the exogenous variables. There are several economic reasons for correlations with the unobservable individual effects, as for example, managerial skills and the innovation behaviour of firms.

[20] Arellano/Bond (1991) use a sophisticated two-step GMM estimator for the autoregressive specification and discuss several test statistics of the validity of the instrumental variable, especially the lack of serial correlation.

product market will decrease markedly). The scale 3 signifies an expected stagnation on the product market.

In Table 1 we report the instrumental variables estimation of the dynamic employment function with a lag structure up to twice lagged variables. Both instrumental variables are used in this estimation ($\ln l_{t-2}$, Δl_{t-2}). The contemporaneous variables of changes in product and process quality are omitted, which avoids endogeneity problems.[22]

The dynamics of the estimation model shows a moderate adjustment velocity of 0.35, and the lag structure is sustained by the test statistics (see t-value and F-test statistics). The indicators for competition (ΔQ_t, ΔP_t) and for demand and the business cycle (BE, ΔY_t) confirm, in general, the theoretical model; the significance of the joint effects of the variables is high.[23]

The estimation results for user costs of capital and wage increases are, as theoretically expected, even if the contemporaneous effects are insignificant. The joint effects, however, are highly significant. The long-term effects of these variables are reported in Table 2. The long-term elasticity of employment in relation to the wage increase amounts to -0.53 which is consistent with other results of similar microeconometric studies.[24] In addition, the elasticity of the user costs of capital is significantly negative at -0.16.

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[21] See e.g. Breitung (1992), pp. 57 who refers to easier estimation methods with a reduced instrumental variable matrix.

[22] We have not instrumented these contemporaneous variables, because we use up to twice lagged variables of changes in product and process quality as regressors. To avoid the multicollinearity problem we must take the three times lagged variables into our instrument matrix, but this leads to a reduction in the number of observations of 25 percent. Also the relationship between the contemporaneous variables and the three times lagged variables is not strong compared with the once and twice lagged variables, so we will again have a multicollinearity problem.

[23] Note the scaling of the variable BE. The sign of the coefficient is therefore negative instead of positive.

[24] See e.g. the panel data study of Arellano/Bond (1991) Breitung (1994), König/Buscher/Licht (1995) and FitzRoy/Funke (1994).

TABLE 1

Employment equation (all variables in first differences)

Sample Period: 1984-1992 (6405 obs.)

Independent variables	Coef.	t-value[a)]	P>|t|	F-Test[b)]
l_{t-1}	0.353	2.243	0.025	
q_{t-1}	0.010	3.367	0.001	F(2,6384)=5.68**
q_{t-2}	-0.003	-1.050	0.294	
te_{t-1}	-0.003	-0.775	0.438	F(2,6384)=0.30
te_{t-2}	0.001	0.272	0.785	
uc_t	-0.018	-1.600	0.110	F(3,6384)=7.68**
uc_{t-1}	-0.035	-2.793	0.005	
uc_{t-2}	-0.050	-3.632	0.000	
w_t	-0.019	-0.261	0.794	F(3,6384)=5.67**
w_{t-1}	-0.124	-1.769	0.077	
w_{t-2}	-0.202	-2.902	0.004	
Q_t	-0.002	-0.128	0.898	F(3,6384)=3.76*
Q_{t-1}	-0.015	-0.769	0.442	
Q_{t-2}	0.039	2.143	0.032	
Y_t	0.269	9.311	0.000	F(3,6384)=58.0**
Y_{t-1}	0.129	2.726	0.006	
Y_{t-2}	-0.169	-3.651	0.000	
P_t	0.264	5.880	0.000	F(3,6384)=11.6**
P_{t-1}	0.035	0.563	0.573	
P_{t-2}	0.057	1.267	0.205	
BE	-0.006	-2.869	0.004	

[a)] We have also calculated the robust variance covariance matrix of the estimators allowing observations to be not independent within a firm (White 1980, Rogers 1993). The standard errors of the estimated coefficients vary next to nothing,, and for the five percent significance level the statements about the significance of each coefficient do not change.
[b)] See Davidson/MacKinnon (1993), ch.7 for the specification of the F-Test in models estimated by instrumental variable methods.
* and ** mean significance at five and one percent significance level, respectively.

The effects of a change in product and/or process quality (Δq_t, Δte_t) are of special interest, since the previous theoretical considerations allow two distinct ways of influence. The estimation confirms a positive impact of product improvements on employment. A product innovation of the preceding period has a significantly positive effect on employment growth at 0.01, whereas the influence of the twice lagged product innovation is negative at -0.003 but with insignificant coefficient. The joint effect is significant and the long-term elasticity of employment in relation to a change of product quality amounts to 0.01 (see Table 2). There is no indication for a great reduction in competition and less output through product innovations. The employment effects of product quality improvements are clearly positive for the innovating firm.

TABLE 2

Long-term elasticity of employment

	Product quality	Wages	User costs of capital
Employment	0.01*	-0.53**	-0.16**

* and ** mean significance at five and one percent significance level, respectively.

A change of the process quality, however, does not influence the firms' labour demand. The single as well as the joint effects are insignificant. Previous estimation results of a labour demand function with exogenous output show negative effects of process innovations on employment.[25] The results of the present estimation with endogenous output decision indicate that the rationalisation effects of process innovations are compensated by positive output effects. In this microeconometric study, there is no evidence that firms which have realised process innovations dismiss employees. But process innovations of the competitors can have a negative impact on the employment of the own firm. Our results indicate that price increases of the competitors have a significantly positive effect on the labour demand of the own firm.

The estimation at issue shows that the effects of product and process quality compared with the effects of demand variables (Y, BE) and factor prices (w, uc) on employment are very modest. The labour demand at the firm level is mainly affected by wages, user costs of capital and the demand side. In our study the effect of innovation activities on employment is partly captured by the expectation variable BE. If the realisation of innovations leads to better turnover expectations, the positive effect of innovation on employment will be underestimated. But this is a problem for further research.

Zusammenfassung

Aus theoretischer Sicht hat die Einführung von Prozeß- und Produktinnovationen gegenläufige Effekte auf die Arbeitsnachfrage des innovierenden Unternehmens. In dieser Arbeit werden die Zusammenhänge zwischen den Innovationsaktivitäten und der Arbeitsnachfrage von Unternehmen anhand des ifo Unternehmenspanels für das westdeutsche Verarbeitende Gewerbe empirisch untersucht. Eine dynamische Arbeitsnachfragefunktion wird mit Hilfe von Instrumentenvariablen geschätzt.

Die wichtigsten Ergebnisse der Paneldaten-Analyse lassen sich wie folgt zusammenfassen: Die Arbeitsnachfrage der Firmen wird hauptsächlich von den Löhnen, den Kapitalnutzungskosten und von der Nachfrageseite beeinflußt. Der Einfluß der Produktinnovationen auf die Beschäftigung ist signifikant positiv. Schließlich finden wir keine empirische Evidenz dafür, daß die Einführung von Prozeßinnovationen Arbeitsplätze in den Unternehmen zerstört.

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[25] See the estimation results of Rottmann/Ruschinski (1997) which are based on the same panel data set.

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