Non-technical summary

One of the principal issues raised in empirical labour economics is how new products and production processes affect employment and the educational composition of the workforce. In the literature it is widely believed that firms which introduce new products tend to have higher rates of growth of output and employment and especially high rates of growth of skilled labour. Employment effects of process innovations are not as obvious. However, the majority of firms introduces product and process innovations simultaneously, thus making it difficult to distinguish between those two types of innovations.

Since the introduction of new processes is often connected with the adoption of new machines, joint implementation of new products and processes should have strong positive effects on the employment of high-skilled labour. More important is the distinction between new products according to their commercial significance. New products can either be new to the firm or new to the market. In the latter case we talk about 'true innovations'. A number of authors emphasize that new market products or alternatively new products in connection with positive revenues are most important for creating employment. Finally, potential endogeneity of innovation in the labour demand function should be taken into account, since any innovation process depends on a number of decisions made by firms. A firm's research and development activity leads to the creation of new goods and services. Also market structure, firm size and labour quality play a decisive role.

This paper investigates the impact of technological innovations on employment expectations of different types of labour in West German manufacturing. Despite the large empirical work on this issue, there are still few studies which focus on different types of educational qualifications and use different innovation indicators at firm level. We distinguish between several types of innovations: introduction of new products and new market products, cost-reducing process innovations and patents. Employment expectations are a function of technological innovations, labour quality and some control variables. Furthermore, we control for possible endogeneity of new market products in the labour demand

equations. To explain new market products, our model takes into account the educational qualification structure of the firm's workforce, R&D activities and other firm characteristics. The main hypothesis are that effects of employment expectation depend on the type of innovation and on educational qualifications. The empirical analysis is based on the fifth wave of the Mannheimer Innovation Panel (MIP) which is also the national part of the second Community Innovation Survey (CIS).

The empirical results suggest that employment expectations differ significantly between innovators and non-innovators. The effects, however, depend on the type of innovation activity and the educational qualifications. As expected, technological innovations have the strongest impact on university graduates. A joint implementation of product and process has stronger employment effects on university graduates. Furthermore, the results show that the introduction of new market products is more important than any other measure of product innovation in determining job creation, in particular for total employment. Labour quality plays an important role in explaining employment expectations. Furthermore, the exogeneity assumption of new market products in the labour demand equations can not be rejected. Finally, the introduction of new market products depend positively on R&D activities and firm size.

Technological Innovations and the Expected Demand for Skilled Labour at the Firm Level[1]

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Abstract. This paper analyses the link between technological product and processes innovations and expectations about future employment for di¤erent types of labour in manufacturing. The empirical model allows for endogeneity of the …rm's innovation decision in the labour demand equations. The system of probit equations is estimated using simulated ML based on 800 West German …rms. The empirical evidence for di¤erent measures of technological innovations indicates that introduction of new market products is more important than any other measure of product innovation in determining the expected employment probabilities for homogeneous labour. Furthermore, as expected, technological innovations have the strongest impact on university graduates. Joint implementation of new products and new processes have a stronger impact on the employment expectations of university graduates than product innovations alone. Labour quality and turnover growth are also important factors of employment growth. Finally, tests of the exogeneity assumption of new market products in the labour demand equations can not be rejected.

Keywords: labour demand, product and process innovations, R&D, educational quali…cation structure, manufacturing.

JEL-Classi…cation: J23, O33, L8

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1. Introduction

It is well known that technological innovations create jobs which require a different skill level. Employment effects of innovations may also be different according to the type of product innovations. For instance, new products can be either new to the firm or new to the market. Brouwer and Kleinknecht (1996) emphasize that the type of innovation most important for the creation of employment and output are new market products. The distinction between product and process innovations is also relevant, in particular with respect to employment. Since most firms introduce product and process innovations simultaneously, it is difficult to evaluate the effects only due to process innovations.

The link between advanced technologies and the demand for skilled labour has been empirically analysed by a number of studies (for a survey of the literature, see Chennells and Van Reenen, 1999). Blechinger et al. (1998) investigate the impact of innovation on employment for eight EU member states based on the first Community Innovation Survey (CIS). König et al. (1994) find for the first wave of the Mannheim Innovation Panel that product innovations have significant positive employment effects. For process innovations there are no positive employment effects. Greenan and Guellec (1996) found for 1000 French firms that product innovations created more employment than process innovations. Similarly Leo and Steiner (1994) and Rottmann and Ruchinsky (1997) found that product innovations have stronger employment effects than process innovations. Based on 1000 West German firms, Roper (1997) found a strong correlation between innovation and output growth, but a less direct link between innovation and employment growth. Research has only for a short time been focussing both on the innovation decision and simultaneously on the labour demand for different types of workers. For instance, Duguet and Greenan (1998) explained the decision for innovation by various input factors and include innovation output as an additional right-hand variable in heterogeneous employment equations.

The analysis of innovation determinants has a long tradition in empirical industrial economics. Among various factors innovation output depends on R&D, demand conditions, firm size and on concentration (see the literature cited in

Cohen and Levin 1989, Brouwer and Kleinknecht 1996) as well as on labour quality (Huiban and Bouhsina 1998, Karlsson and Olssen 1998). Doms, Dunne and Troske (1997) also pointed out that firms that use skilled labour intensively are more likely to adopt new technologies. There are numerous empirical studies on innovation determinants for German firm data.[1]

This paper examines the relationship between firms' employment expectations for different types of labour and the innovation output by using firm data for the West German manufacturing industries. Since longer time series for different types of educational qualifications have not been available, we focus on employment expectations rather than on actual employment growth rates. The system of equations is assumed to be of probit types explaining employment expectations for different types of educational qualification. Since the error terms of employment expectation equations are likely to be correlated, the resulting system of equation is a multivariate probit model. The Geweke-Hajivassiliou-Keane (GHK) simulated maximum likelihood estimator is employed to estimate the multi-dimensional integrals required by the probit structure of different employment equations.

A special focus is directed to the measurement of innovation. Innovations vary enormously in their technological significance (see Brouwer and Kleinknecht 1996). The impact of different innovation indicators will be analysed using a variety of innovation measures [i.e. new product introduction, patent, new market product, cost-reducing process innovation]. Another special focus is directed to potential endogeneity of technological innovation (i.e. R&D dependence of technological innovations) in the labour demand equations. Among other factors, R&D intensive firms are more likely to bring new products to the market. Since non-innovative firms are not compelled to answer to all questions about innovation input, endogeneity of product or process innovations can not be examined. Restricting the sample to innovative firms only allows us to control for possible endogeneity of some forms of product innovations, for instance new market

[1] See for example, Beise and Stahl (1999) who analyze the innovation behaviour using the fourth ZEW MIP wave and Bertschek and Lechner (1998) who investigate the innovation behaviour using IFO innovation panel data on 1000 West German firms.

products. To account for endogeneity of new market products in the expected labour demand function an innovation selection equation is added to the system of equations.

The data is drawn from the …fth wave of the Mannheim Innovation panel (ZEW-MIP), which has previously been analysed by Janz and Licht (1999). Note that the …fth ZEW-MIP wave is the national survey corresponding to the second wave of the Eurostat Community Innovation Survey (CIS). As in most other empirical studies there are some data problems. Considering …rm data, like in general we do not have information about wages of di¤erent types of educational quali…cations. Furthermore, data on the use of information technology is not available in the 1997 ZEW-MIP. The study focuses on West German manufacturing for at least two reasons. First, the 1997 ZEW-MIP gathered detailed information about innovation output indicators as well as employment expectations for di¤erent types of educational quali…cation. Second, for manufacturing …rms the distinction between product and process innovation is less di¢cult than for service …rms. Finally, the West German manufacturing sector itself is interesting. The 1990s were marked by highly divergent cyclical trends. Following the deep recession in the early 1990s, employment of unskilled workers decreased between 6 and 10 percent per year during the 1992 - 1997 period (see Table A6 in Appendix). The demand for university graduates was also descending. Manufacturing real value added growth in 1997 was 3:6, percent the corresponding …gure in 1998 was 5:2 percent, the highest growth rate since 1990. Despite the relatively high output growth, manufacturing shows weak employment growth, and an employment structure shifting towards university graduates. Growth in high-skilled jobs has been very dynamic in manufacturing, showing annual growth rates of 3 percent and more. In contrast, the total number of employees remained stable during 1998 for the …rst time since 1991 (see Table A6 in Appendix).

The layout of the paper is the following. Section 2 outlines the econometric model. Data used for the study is discussed in section 3. Section 4 presents the results for multivariate probit models. Section 5 gives the conclusions.

2. The modelling framework

2.1 Factor demand model

To examine the relationship between the employment expectations for di¤erent types of labour and technological innovations a factor demand model based on a cost function can be derived. There are also indirect employment e¤ects of product innovations. Employment creation depends among other factors on the possibility of substitution between new and old products (see Katsoulacos 1984). Moreover, product innovations not only a¤ect the labour demand but would also stimulate output growth due to higher pro…ts. Here we focus on the direct employment e¤ects of technological product innovations for a given output level. Rather than investigating the relationship between the levels of di¤erent types of labour as a function of the technology level, we develop a model that relates the change in di¤erent types of labour to the introduction of technological innovations. Assuming zero substitution possibilities between di¤erent types of labour the short-run labour demand system for di¤erent types of labour may be described as:

$$¢l_i^m = f_1(¢p_i^m; ¢y_i; ¢inno_i; ®) + ³_i \quad (2.1)$$

where i,...,N, is the …rm index and $¢l_i^m = (¢l_i^1; ¢l_i^2; ¢l_i^3)$ are the employment growth rates for di¤erent types of labour. The vector of labour input is de…ned as follows: $¢l_i^1$ denotes university graduates, $¢l_i^2$ denotes masters and technicans and $¢l_i^3$ denotes total number of employees.[2] Factor price changes for di¤erent types of labour are labeled as $¢p_i^m$: Growth of total output is $¢y_i$: The innovation output, $¢inno_{it}$; is de…ned as a discrete event, which describes, whether or not …rms introduce technological innovations. The parameter vector to be estimated is denoted by ®: Unfortunately, information about employment growth rates in period t+1 is not available. Instead, categorical information on

[2] It would be preferable to distinguish between high-skilled, medium and unskilled workers (see Falk and Koebel 1999). Since information on the educational quali…cation structure is only available for white collar workers, di¤erentiating between university graduates and masters on the one hand and technicans on the other hand is the maximum we can do with the data.

expected employment growth is available. Consequently, ordered probit models can be used to estimate employment expectations (see Kaiser 1999). Since only 5 percent of the firms expect a decrease in both university graduates or masters and technicans, little information will be lost if a binary measure of employment expectations is used instead.[3] Consequently, a dummy variable whether or not firms plan to increase employment for different types of labour is substituted for the employment growth rate. Furthermore, I assume a time lag between expected employment growth and the right-hand variables. Adding a vector of firm characteristics, z_{it}, the factor demand system is given by:[4]

$$E(\Delta l^m_{it+1}) = f_2\left(\Delta inno_{it;t-1}; \Delta y_{it}; \Delta l^m_{it}; \frac{L^H_{it}}{L_{it}}; z_{it}; \alpha\right) + \varepsilon_{in}. \qquad (2.2)$$

where subscript t denotes time. The variables are denoted as:

$E(\Delta l^m_{it+1})$	expected employment growth in t+1 (1997-99) at time t,for m=1,..3.
$\Delta inno_{it;t-1}$	indicator for innovation, three year interval, 1994-96
Δy_{it}	current output (sales) growth rate, 1996
Δl^m_{it}	current employment growth rate, 1996
L^H_{it}/L_{it}	university graduates or high-skilled labour share, 1996
z_{it}	size, sector and other control variables, 1996

The dependent variable is represented by the expected employment growth for different types of labour in the following period, $E(\Delta l^m_{it+1})$. The right-hand variables are indicators for innovation, labour quality measured as the high-skilled or the university employment share, current output and employment growth rate as well as the vector of control variables, z_{it}. Since there is a time lag between employment expectations and the right-hand variable, causation clearly goes from innovation to employment. The expected derivatives are as follows:

[3] In principle, it is possible to use actual employment growth rates instead of employment expectations. Employment levels for the total number of employees are available for the period between 1994 and 1996 and the educational structure of the workforce is available for the period between 1995 and 1996, so that one or two year growth rates can be calculated. There are two arguments opposing this: First, one year growth rates may be very noisy. Second, the time period for the employment growth rates as well as the introduction of both product and process innovations lies within 1994 and 1996. This would cause a simultaneity problem.

[4] Since there are no wages in the employment equations, this approach is a very restricted specification of factor demand.

$$\partial E(\Delta l^{m}_{i,t+1})/\partial \Delta inno_{it,t-1} > 0;\ \partial E(\Delta l^{m}_{i,t+1})/\partial \Delta y_{it} > 0;$$
$$\partial E(\Delta l^{m}_{i,t+1})/\partial \Delta l^{m}_{it} > 0; \partial E(\Delta l^{m}_{i,t+1})/\partial \frac{L^{H}_{it}}{L_{it}} > 0 \qquad (2.3)$$

The main hypothesis is that technological innovations should be strongly related to the employment expectations for different types of labour, $\partial E(\Delta l^{m}_{i,t+1})/\partial \Delta inno_{it,t-1} > 0$; for $m = 1, 2, 3$. The effects of product innovations should be stronger for university graduates and masters as well as for technicans than for total employment. A positive relationship between employment expectations and the high-skilled employment share is also expected. At the sectoral level employment growth depends positively on the skill intensity. A measure of output change is included in all employment equations. Output should be positively related to employment expectations of different types of labour. Two measures of output change are available, the current output growth rate, Δy_{it}, and an ordered categorical variable for expected output. Since it is likely that causality goes in both directions, current output growth rather than expected output should be included in the employment equations. Furthermore, since it is likely that employment expectations depend on realized employment changes in the past, the observed one year employment growth rate can be included.

Estimating the effects of technological innovations raises the question about definition and measurement of innovation output (see Cohen and Levin (1989), Crepon et al. (1998), Meyer-Krahmer (1984) and the literature cited in Symeonidis (1997)). According to Brouwer and Kleinknecht (1996) product innovations can be divided into innovations that are new to the firm and innovations that are new to the market. Furthermore, information about the introduction of a new product can be combined with information about whether or not firms gained positive revenues by the introduction of new products. This measure may give some indication of the commercial significance of the product change. Patents are an alternative indicator for innovation output. The single measure for product innovation can be replaced by various terms of interaction with other types of product or process innovations:

$$\Delta inno_{it;t-1} = g_1(\Delta new\ prod_{it;t-1}; rev_{it} \times \Delta new\ prod_{it;t-1}) \qquad (2.4)$$

$$\Delta inno_{it;t-1} = g_2(\Delta new\ prod_{it;t-1}; \Delta new\ market_{it;t-1} \times \Delta new\ prod_{it;t-1})$$

$$\Delta inno_{it;t-1} = g_3(\Delta new\ prod_{it;t-1}; \Delta process_{it;t-1} \times \Delta new\ prod_{it;t-1})$$

$$\Delta inno_{it;t-1} = g_4(\Delta new\ prod_{it;t-1}; \Delta patent_{it;t-1} \times \Delta new\ prod_{it;t-1})$$

where the variables are defined as follows:

$\Delta new\ prod_{it;t-1}$	introduction of new or improved products (0/1), 1994-96
rev_{it}	whether or not firms gained positive revenues due to new or radically changed products, (0/1), 1994-96
$\Delta new\ market_{it;t-1}$	whether or not firms introduced new market products, (0/1), 1994-96
$\Delta process_{it;t-1}$	either process innovations, (0/1), 1994-96 or cost reducing process innovations, (0/1), 1994-96
$\Delta patent_{it;t-1}$	patent application, (0/1), 1995-97

Various indicators for product innovations are used: $\Delta new\ prod_{it;t-1}$ denotes whether or not firms introduced new or improved products; rev_{it} denotes whether or not firms gained positive revenues from the new or radically changed product and $\Delta new\ market$ denotes whether or not firms introduced new market products. The first measure for product innovation, $\Delta new\ prod_{it;t-1}$, covers new or improved products. The second product innovation measure is $\Delta new\ prod_{it;t-1} \times rev_{it}$ and the third is $\Delta new\ prod_{it;t-1} \times \Delta new\ market_{it;t-1}$: We expect that the employment effects are stronger for new market products as well as for new or radically changed products with positive revenues.

An additional test analyzes whether a joint implementation of new products and processes innovations will have different employment effects for different types of labour. Process innovations are often carried out by the replacement of existing capital with new machines. This clearly favours high-skilled labour rather than unskilled labour.[5] Two further interaction terms are introduced. The first combines product and process innovation. The second is a combination of product innovations and cost reducing process innovations ($\Delta new\,prod_{it;t-1} \times cost\text{-}red_{it}$). The latter is defined as whether or not firms achieved a cost reduction by the introduction of new processes.

2.2 Innovation equation

Innovation output is not exogenous to the firm. Estimation of the determinants of the employment expectations must take into account the selection bias thereby induced. To account for this bias, an innovation selection equation is introduced. Innovation determinants have been clearly identified in the literature (see literature cited in Cohen and Levin 1989 and Symeonidis 1997). The usual innovation determinants are R&D intensity, firm size, market structure, capital intensity, and advertising expenditures. Innovation may also be positively related to the firms' labour quality. According to Huiban and Bouhsina (1998), a number of activities closely related to R&D activities require formal knowledge. They propose the engineering share as an additional variable in the innovation equation.

Unfortunately, non-innovative firms are not compelled to answer to all questions about innovation input, so that the relationship between innovation output and innovation inputs can only analysed for firms that carried out some form of product or process innovations. One solution is drop non-innovative firms from our sample and restrict the extended model to innovative firms. Another solution is to introduce a R&D selection equation. Since exclusive restrictions are hard to find, we restrict the following analysis on the restricted sample and only control for potential endogeneity of some forms of innovations (new market products). New market products can be related to R&D activities, the high-skilled employment share, size and sector dummies and a diversification variable:

$$\Delta inno_{it} = f_2\left(L^H_{it}/L_{it}; R\&D_{it}; sub_{it}; div_{it}; z_{it}; \beta\right) + \varepsilon_i. \qquad (2.5)$$

[5] However, preliminary calculations suggest that only 1% of the innovating firms introduce process innovations but no product innovations. Therefore, it makes little sense to distinugish between product and process innovations.

where the variables are defined as follows:

$R\&D_{it}$	whether or not firms are engaged in R&D, distinction between continuously and occassionally engaged in R&D
sub_{it}	whether or not firms received loans, 1996
div_{it}	diversification index
z_{it}	firm size and industry dummies

The identifying variables consist of the R&D and the diversification variable. R&D is measured as a dummy variable whether or not firms are continuously engaged in R&D. One important point concerns the distinction between permanent and occasional engagement in R&D. According to Brouwer and Kleinknecht (1996), firms that are permanently engaged in R&D are more likely to be engaged in innovation compared to those occasionally engaged in R&D. Consequently, a second R&D dummy variable can be included indicating whether firms are occasionally engaged in R&D. Alternatively, R&D activity can be measured as R&D intensity. The clear advantage of the first measurement concept is that the R&D dummies do not refer to a specific period of time. Moreover, the inclusion of current R&D intensity in the innovation output equation can be criticized because of the adjustment lag between innovation output and R&D investment. Furthermore, the sales share of the most sales-intensive product is taken as an indicator for the degree of diversification. Concentration measures are not included in the model. Concentration ratios are often found to be insignificant (see Brouwer and Kleinknecht 1996 and the literature cited in Symeonidis 1997). Furthermore, the sample size may be too small to include concentration ratios on the four digit level.

The expected derivatives are as follows:

$$\begin{aligned} \partial\, inno_{it}/\partial(L^H_{it}/L_{it}) &> 0; \partial\, inno_{it}/\partial R\&D_{it} > 0; \\ \partial\, inno_{it}/\partial sub_{it} &> 0; \partial\, inno_{it}/\partial div_{it} < 0; \end{aligned} \tag{2.6}$$

Firms that are continuously engaged in R&D should have a higher innovation probability. Since employment of university graduates or masters and technicans may have a particularly beneficial impact on the firms' innovation capability, due to the link to higher education institutes, we expect a positive coefficient on the high-skilled employment share. Finally, we expect the firm size as well as the subsidy dummy to have a positive effect (sign), but diversification to have a negative effect on the innovation probability.

Before proceeding, several caveats are in order. There are some problems with formal R&D activities as a measure of innovation input. Firms need not only perform R&D for a successful new product introduction, but also activities in related innovation activities. Especially within small firms, informal R&D is carried out (see Kleinknecht 1987). One way to overcome this problem is to use the innovation expenditure sales ratio as an alternative measure. Another limitation of the analysis is, that for some innovation outputs such as innovative sales quantitative and ordered categorical information is available. Here we use only qualitative (binary) information at the cost of losing quantitative information.

2.3 Estimation techniques of the multivariate probit model

The argument of estimation of a system of equations is stronger if either theory predicts cross-equation restrictions (i.e., symmetry restrictions) or if an endogenous variable is included on the right hand-side. Since in absence of factor prices symmetry restrictions do not exist, endogeneity of innovation is more important. There are few applications of multi-equation probit models with one endogenous dummy variable on the right-hand-side. One exception is Greene (1998), who uses the bivariate probit model with one endogenous variable taken as an additional regressor on the right hand side. The multivariate probit model is a generalization of the bivariate probit model.[6] The multivariate model contains four structural equations: three employment expectation equations and one innovation equation (subscript t is suppressed for convenience):[7]

$$y_m^* = \gamma_m y_n + \beta_m' x_m + \varepsilon_m; \quad m = 1; 2; 3 \qquad (2.7)$$

[6] See Greene (1997) for a description of the multivariate probit model.

[7] In principle, the model can be easily extended by including additional innovation equations for different types of educational qualifications and different innovation indicators. Note, that the inclusion of further employment equations is not without cost. The amount of computation increases more than linearly with the number of equations.

$$
\begin{aligned}
y_n^* &= \beta_n' x_n + \varepsilon_n; \; n = 4 \\
y_{m} &= 1 \text{ if } y_m^* > 0; \; y_{n} = 1 \text{ if } y_n^* > 0 \\
\varepsilon' &= [\varepsilon_m; \varepsilon_n] \sim N(0; \Sigma)
\end{aligned}
$$

where y_m^* represents the employment expectations for different types of educational qualifications during the period between 1997 and 1999 and y_n^* denotes indicators for technological innovations. The vector x_m contains control variables. The vector x_n contains both control and identifying variables. The latter contains variables which are assumed to be exogenous and are not included in the employment equations. ε' is assumed to be jointly four variate normally distributed with zero mean vector. Given that the variance is 1, the variance-covariance matrix, Σ; consists of a correlation matrix including six free parameters:

$$
\Sigma = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ & 1 & \rho_{23} & \rho_{24} \\ & & 1 & \rho_{34} \\ & & & 1 \end{pmatrix} \tag{2.8}
$$

For the multivariate probit model marginal effects of the following form can be obtained : The expected value of Y_1 given that all other Y's equal 1 is:

$$
E[Y_1 | Y_2 = 1; ...; Y_4 = 1] = Prob(Y_1 = 1; ...; Y_4 = 1) / Prob(Y_2 = 1; ...; Y_4 = 1) \tag{2.9}
$$

Alternatively, the expected value of Y_1 is given that innovation equals one, $Y_4=1$, but expected employment for total number of employees as well as for masters and technicans equals 0, $Y_2=0$, $Y_3=0$. All effects can be calculated at the means of the right-hand variables.

The multivariate probit model offers several testable hypotheses. The first is that the error terms between the innovation equation and each employment expectation are correlated. It is easy to see, that the multivariate probit model assuming exogeneity arises as a special case with $\rho_{14} = \rho_{24} = \rho_{34} = 0$. When the error terms are correlated, excluding the innovation selection equation will not yield consistent estimates of the parameters on new market products. A

Wald test or a likelihood ratio test can be carried out to test whether innovation is exogenous. The null hypothesis $H_0 : \rho_{14} = \rho_{24} = \rho_{34} = 0$ is tested against $H_1 : \rho_{m4} \neq 0$; for m=1,..3. The number of degrees of freedom is 3. In case of exogeneity of innovation, the coefficient on innovation in the expected labour demand equations can be estimated consistently by simple univariate probit models. However, the error-terms in the employment equations of different types of labour may be still correlated because of unobserved firm specific characteristics. Therefore, estimation by seemingly unrelated probit regression should be preferred in order to exploit all information and provide the most efficient estimator. An additional Wald test can be performed to test the correlation of the error-terms in the three equation model. If the null of no correlation between the error term in the innovation equation and each employment equation is rejected, independent binary probit models are adequate.

The multivariate probit model described above (2.7) will be estimated by the simulated MLE separately for different measures of innovation output. The simulated MLE method will be described briefly in the following. The probability for the random vector u is given by:

$$\Pr(a < u < b) = \int_{a}^{b} \cdots \int_{a_2}^{b_2} \int_{a_1}^{b_1} \phi_J(u)du_i \qquad (2.10)$$

where u is assumed to be distributed multivariate normal with mean 0 and variance Ω and ϕ_J is the density function of a J-variate normal distribution with the correlation matrix Σ: It is obvious that in the case of more than three probit equations more than three levels of numerical integrations are required. Therefore, the integral can not be calculated analytically and exact MLE is not possible. Instead, the probability is approximated through simulation:[8]

$$\Pr(a < u < b) \approx \frac{1}{R} \sum_{r=1} \prod_{k=1} Q_{rk} \qquad (2.11)$$

where R are the number of replications and Q_{rk} are univariate probabilities.

[8] See Hajvassiliou (1993), Keane (1994) and Greene (1997: 192) for an exposition of the simulated maximum likelihood estimator.

The idea of the simulated MLE method is that the integral of interest represents the probability of an event in a population. Therefore, we only need to replace the choice probabilities in the likelihood function by the simulated probabilities. The first step is, that u in the left hand side of expression (2.11) is replaced by a random vector of independent standard normal variables ε multiplied by a lower triangular matrix L. The probability on the left hand side in (2.11) can now be written as:

$$P(a < L\varepsilon < b) = P[a_1 < l_{11}\varepsilon_1 < b_1; a_2 < l_{12}\varepsilon_1 + l_{22}z_2 < b_2; \ldots \tag{2.12}$$

$$a_k < l_{1k}\varepsilon_1 + \ldots\ldots + l_{kk}\varepsilon_k < b_k]$$

where L is the lower triangular Cholesky factor of $\Omega = LL'$ and $l_{km}; a_i$ and b_i are the corresponding elements of L, a and b. The triangular structure of constraints makes it easier to simulate the probabilities. After rearranging terms in equation (2.12), the intervals defining the events can be written as:

$$A_1 = \left\{ \frac{a_1}{l_{11}} < \varepsilon_1 < \frac{b_1}{l_{11}} \right\} \tag{2.13}$$

$$A_2 = \left\{ \frac{a_2 - l_{12}\varepsilon_1}{l_{22}} < \varepsilon_2 < \frac{b_2 - l_{12}\varepsilon_1}{l_{22}} \right\}$$

$$A_k = \left\{ \frac{a_k - l_{1k}\varepsilon_1 - \ldots - l_{k-1;k}\varepsilon_{k-1}}{l_{kk}} < \varepsilon_k < \frac{b_k - l_{1k}\varepsilon_1 - \ldots - l_{k-1;k}\varepsilon_{k-1}}{l_{kk}} \right\}$$

Combing equation (2.12) and equation (2.13) the probability can be expressed as the product of univariate probabilities:

$$P(a < L\varepsilon < b) = P(A_1)P(A_2 \mid A_1)P(A_3 \mid A_1; A_2)\ldots\ldots P(A_n \mid A_1; \ldots\ldots; A_{n-1}) \tag{2.14}$$

The choice probabilities in equation (2.14) will be replaced by simulated probabilities:

$$P(a < \varepsilon < b) = \frac{1}{R}\sum_{r=1} P(A_1)P(A_2 \mid \varepsilon_{1r})P(A_3 \mid \varepsilon_{1r}, \varepsilon_{2r}).....P(A_k \mid \varepsilon_{1r}, ..., \varepsilon_{k-1,r}) \tag{2.15}$$

$$= \frac{1}{R}\sum_{r=1}\prod_{k=1} Q_{rk}$$

where R are the number of replications and ε_{1r} are drawn sequentially from truncated independent standard normal distributions. Once the ε_{1r} are drawn the product of the estimated probabilities is calculated (see Greene 1997: 196):

$$Q_{r1} = \Phi\left(\frac{b_k}{l_{kk}}\right) - \Phi\left(\frac{a_k}{l_{kk}}\right) \tag{2.16}$$

$$Q_{r2} = \Phi\left(\frac{b_k - l_{1k}\varepsilon_1}{l_{kk}}\right) - \Phi\left(\frac{a_k - l_{1k}\varepsilon_1}{l_{kk}}\right)$$

$$Q_{rk} = \Phi\left(\frac{b_k - \sum_{m=1}^{k-1} l_{km}\varepsilon_{rm}}{l_{kk}}\right) - \Phi\left(\frac{a_k - \sum_{m=1}^{k-1} l_{km}\varepsilon_{rm}}{l_{kk}}\right)$$

where Φ is the cumulative distribution function of a standard normal distribution function. This process is repeated R times and the average is taken as the approximate probability. Börsch-Supan and Hajivassiliou (1993) proved that the probability simulator is an unbiased estimator of the true probability. One problem of the simulation methods is the creation of noise. Hajivassiliou (1997) noted that accuracy of the probability simulators can be increased by the number of replications per estimation. However, the increase in computer time may become unacceptably large. Furthermore, the amount of computation in the multivariate probit models varies both linearly with the number of observations and the number of replications. It also varies somewhat more than linearly with the number of independent variables (Hajivassiliou 1997).

3. The data

The data set employed for the subsequent empirical analysis contains the fifth wave of the Mannheim Manufacturing Innovation panel 1997 (MIP). The main intention of this survey was to investigate the innovation behaviour of manufacturing firms (for details see Janz and Licht 1999). Most of the continuous variables, such as R&D intensity or innovation sales ratio are from 1996. For some variables, i.e. total sales and total employment, information about the period of 1994 to 1996 is available. Information about the educational qualifications of the workforce is available for the two year period of 1995 and 1996. Approximately 2400 firms participated in the fifth wave of MIP from which non-manufacturing firms as well as East German firms are removed. Based on aggregate figures, East German manufacturing represents only one tenth of total German manufacturing.

The first set of dependent variables consists of employment expectations for different types of labour. In the 1997 questionnaire managers are asked about their expectations for total sales, total employment and different types of educational qualifications in three years, i.e. from the period 1997 to 1999. Five categories for employment expectations can be distinguished: strong increase, slight increase, unchanged, slight decrease, strong decrease. For each employment variable the 5 categories are regrouped into two categories: expected increase equals '1', unchanged or decrease equals '0'. Since only very few firms expect employment to decrease, the distinction between the decreasing employment category and the stable employment category is not very important. Table A3 in Appendix, shows that only 3.6 percent of the firms expect the employment of university graduates with an engineering or a natural science degree to decrease. For the social science group 5.0 percent of the firms expect a decrease.

Since information on educational qualification classes is only available for white collar workers, separating labour into two groups (university graduates on one hand and masters and technicans on the other hand) is the maximum that we could implement with this data. Expected change in university graduates is constructed as follows. Two groups of university graduates can be distinguished:

the …rst group consists of workers having attained a university degree or a higher polytechnical degree ("Fachhochschule") in engineering or natural science and the second group contains graduates with a degree in social or other sciences. Following Kaiser (1999), the engineering/natural science and the social science group are regrouped into one group of university graduates. The reason is that in manufacturing the share of university graduates (including higher technical college graduates) who gained a natural science or engineering degree amounts to 76 percent of all university graduates (based on calculations of the 1995 micro census, see Table A7 in Appendix). If a …rm expects an increase in either the engineering/natural science or the social science group the variable expected change is recoded 1 and 0 else. Firms are also assigned to the "1" group when they show decreasing employment for one university graduates group but increasing employment for the other university graduates group. Only very few …rms expect increasing employment for engineering/natural science graduates but decreasing employment for the social science group (see Table A4 in Appendix). The most common answer is stable employment for both groups of degrees. 51 percent of the …rms answered that employment for both groups remains stable for the period of 1997 to 1999. The second most frequent answer is an expected increase in the engineering/natural science group and stable employment in the social science group 24 percent. 13 percent of the …rms considered an increase in both groups. The other dependent variables are considered to be expected employment change for the total number of employees and expected employment for masters and technicans. Both variables are also recoded to 1 if …rms plan to expand the total number of employees for the period of 1997 to 1999 and 0 if the employment is stable or falling.

The second set of dependent variables contains di¤erent innovation indicators for the 3-year period introduced between 1994 and 1996.[9] In general, technological innovations can be divided into process and product innovations. For product innovations three de…nitions can be used. The …rst measure are new or better products that had not been produced before and were introduced during the period of 1994 and 1996. These products may be new to the …rm, but they may

[9] The questionnaires are listed in Table A1 in Appendix.

also be new to the market. The second product innovation measure combines information on production innovation and the revenues due to the introduction of the new and radically renewed product. Innovative firms are asked about their percentage of sales share in 1996 achieved by the new or radically changed product.[10] Approximately 15 percent of the firms in the estimation sample refused the answer about the revenue share, mostly product innovators. The second product innovation measure equals 1 if firms introduce new products and gained positive revenues by the new or radically changed product, and otherwise zero. Finally, the third product innovation measure refers to new market products. It covers the introduction of new or noticeably improved products which are not only new to the firm but also new to the firm's market. As Brouwer and Kleinknecht (1996) have already noted, new market products allow us to distinguish between imitations of innovations and true innovations. The introduction of products new to the firm is often based on some degree of imitation, whereas products new to the market may be considered as true innovations. In the questionnaire all firms were asked about whether or not new market products are introduced.[11] Finally, another innovation measure, the application for a patent between 1995 and 1997, is considered. For the process innovation indicators two definitions can be used. The first definition covers process innovations and equals 1 if new processes are introduced during the period between 1994 and 1996. The second definition comprises those firms, which reported cost reductions due to the introduction of new processes.[12]

The left hand variables in the innovation equations may be a dummy variables indicating whether or not firms are either continuously or occasionally engaged in R&D. Alternatively, R&D intensity or the innovation expenditures sales ratio can

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[10] Firms are also questioned about the turnover due to new and incrementally improved products in 1996.

[11] Similar as before, the question whether new market products are included or not can be combined with the question whether firms gained positive revenues by the product. This question is only asked to firms with new market products. Among the innovators approximately 20 percent of the firms refused the answer about revenues on new market products. The remaing firms all have positive revenues.

[12] Approximately 11.5 percent of the firms refused the answer about cost reducing process innovations. In case of non process innovative firms missing values are replaced by "0".

be used as a substitute for the R&D dummy variables. Other control variables are the sales share of the product most intensive in sales, and a complete set of sector and size dummies. In distinguishing between …rm size, dummy variables based on the number of full time equivalent workers are used. Five classes of size are considered: 5 ¡ 49, 50 ¡ 99, 100 ¡ 249, 250 ¡ 499, and more than 499 employees. Three measures of the high-skilled share are calculated. The …rst employment share contains workers with a university degree. The second one covers masters and technicans and the third contains both. Each high-skilled share is expressed as the percentage of the sum of all the …ve skill groups.

The initial sample for West German …rms contains information on 1600 …rms. Exclusion of …rms belonging to sectors other than manufacturing reduces the sample to 1430 …rms. Following Beise and Stahl (1999), …rms with less than 5 employees are excluded, which leaves us with 1334 …rms (see Appendix for the missing information on the variables). Next, …rms with missing information about the dependent variables are dropped from the sample. Incomplete information on …rms' expectations for the change in the number of total employment, employment by educational quali…cation and sales led to a sample reduction to 959 …rms. A further sample reduction is caused by missing information on R&D activities, subsidies and the sales share of the most sales intensive product. For approximately 90 …rms the innovation sales ratio multiplied by the factor 0:5 was substituted for the R&D intensity. Finally, the estimation sample contains 837 West German manufacturing …rms. If one restricts the sample for which information on the other product innovation indicators are available, the sample reduces to 768 …rms in case of new markets. Excluding non-innovators reduces the sample to 574 …rms.

Table 1 shows descriptive statistics for both estimation samples. Average employment of the manufacturing …rms is 450 with one quarter in the smallest size category (5 ¡ 49 employees). Employment growth rate in 1996 amounts to ¡ 1:4 percent. For aggregate West German manufacturing the 1996 employment growth rate amounts to ¡ 3:3 percent (see Table A6 in Appendix). This may indicate that growing …rms are somewhat overrepresented in the estimation sample. In 1997 63 percent of the manufacturing …rms expect sales to increase for the medium-term period 1997 to 1999. This clearly corresponds to the economic upturn in overall manufacturing. Based on aggregate …gures manufacturing value added grew by 3:2 percent in 1997 and 5:2 percent in 1998.

While in 1997 42 percent anticipated an increase in the employment of university graduates for the period between 1997 and 1999, only 21 percent of the …rms expected total employment levels to increase. Thus, the majority of the manufacturing …rms expected unchanged or decreasing numbers of total employees. For the masters/technicans 31 percent of the …rms expected employment to increase. Approximately 77 percent of the respondents indicated that they carried some form of product or process innovations over the period between 1994 and 1996. The introduction of new and improved products is reported by 75 percent of the …rms. This number falls to 63 percent when new or radically changed products combined with positive revenues are considered. About 41 percent of the …rms introduced new market products. Furthermore, only 2:3 percent of the …rms introduced new processes not combined with product innovations making the distinction between product and process innovations less meaningful. Cost reducing process innovations combined with new and improved products are reported by 48 percent of the …rms. Patents applications accounted for 45 percent of the estimation sample. In the questionnaire R&D performing …rms can be distinguished into …rms that are occasionally or continuously engaged in R&D. Approximately 43 percent of the …rms carried out continuous R&D activities. One fourth of the …rms reported that they are occasionally engaged in R&D.

Table 1 also includes high-skilled employment shares. In 1995, the portion of university graduates as percentage of the total of employees amounts to 9:0 percent, which is fairly comparable to 8:7 percent employment share based on the Labour Force Survey (see Table A5 in Appendix). The masters and technicans employment share is 8:0 percent which is slightly below the calculations based on the Labour Force Survey. One explanation for the lower masters and technicans share in …rm level data set is that only white-collar workers are covered. Labour Force Survey calculations suggests that approximately 20 percent of all masters and technicans are blue-collar workers. Altogether, the high-skilled proportion (masters and technicans as well as university graduates) amounts to 18:3 percent

Table 1: Summary Statistics, Means (percent)

		full sample		restr. sample	
	period	obs.	means	obs	means
employment (FTE), numbers	96	837	450	574	571
total sales (DM million)	96	837	141	574	181
…rms expectations (increase=1,decrease or unchanged 0) (percent)					
expected employment	97-99	837	21:4	574	23:0
expected university graduates	97-99	837	41:8	574	49:7
expected master/technicans	97-99	837	30:8	574	34:8
innovation indicators (0/1)					
product innovation only, (pd)	94-96	837	12:7	574	16:9
pd and process innovation	94-96	837	62:2	574	80:8
process innovations only	94-96	837	2:3	574	3:3
no innovations	94-96	837	22:8	574	0:0
pd£positive new prod. revenues	94-96	729	63:1	483	85:7
new market products	94-96	768	40:6	574	54:2
pd and cost-reducing process inno.	94-96	803	47:7	544	63:4
right-hand variables (percent)					
expected sales (0/1)	97-99	837	63:0	574	67:9
growth rate total sales	95; 96	533[a]	6:8; 3:1	377[a]	7:0; 2:6
university graduates share	95; 96	837[a]	9:0; 9:7	574[a]	10:2; 10:9
master/technicans share	95; 96	837[a]	8:0; 8:6	574[a]	8:5; 9:1
growth rate university grad.	96	679	9:2	491	9:8
growth rate masters/techn.	96	645	6:5	458	6:5
growth rate total employ.	95; 96	756[a]	0:0; ¡ 1:4	516[a]	0:0; ¡ 1:7
R&D doing …rms, continuous	[b]	837	45:7	574	59:8
R&D doing …rms, occasional	[b]	837	23:2	574	30:0
R&D intensity	96	837	1:6	574	2:2
sales share of prod 1	96	837	62:5	574	58:8
subsidies (0/1)	96	837	16:8	574	22:8
size 1 (0/1): 5 · L < 50	96	837	25:6	574	19:5
size 2 (0/1): 50 · L < 100	96	837	15:4	574	14:3
size 3 (0/1): 100 · L < 250	96	837	21:5	574	22:3
size 4 (0/1): 250 · L < 500	96	837	19:8	574	20:7
size 5 (0/1): L ¸ 500	96	837	17:2	574	22:6

Notes: [a]Observations for 1996 values. In 1995 less observations are available due to missing values.[b]Do not refer to a speci…c time period. Dummy variables are multiplied by 100.

Source: ZEW Mannheim Innovation Panel, …fth wave, 1997, own calculations.

in 1996 and 17:0 percent in 1995. Thus, the move towards skilled labour can even be observed during the short two year period. The move towards high-skilled labour is more pronounced for university graduates than for masters and technicans. Based on Labour Force Survey calculations, the proportion of university graduates increased by 1:7 percentage points, whereas the masters and technicans employment increased by 0:5 percentages points between 1991 and 1995 (see Table A5 in Appendix). The sectoral breakdown again shows that the high-skilled employment shares are fairly similar between both data sources (MIP 1997 and micro cenus).

Table 2 presents simple cross-tabulations between employment expectations and di¤erent innovation output indicators. The percentage of …rms with an expected increase for one of three employment categories is compared between innovators and non-innovators. This table also includes statistical tests examining the relationship between the di¤erent performance expectations and di¤erent innovation activities. Cramer's V provides an index of the strength of the relationship between two variables.[13] Furthermore, the two-sided Fisher's exact marginal signi…cance levels can be calculated to determine if there are nonrandom associations between technological innovations and employment on one hand and technological innovations output on the other hand. In general, innovators reported higher output and employment expectations than did non-innovative …rms. In particular, job creation for university graduates is actually more common in the innovative group: between 49 and 57 percent expect employment to increase, depending on the type of innovation. For the non-innovative group only between 21 and 33 percent expect the employment of university graduates to increase. Cramer's V indicates that expectations for high-skilled labour and di¤erent types of innovations are correlated with a positive sign. The strength of the index ranges between :18 and :25 for the pairs of high-skilled employment and innovation. The Fisher tests shows, that the di¤erence between innovators and non-innovators is signi…cant in all cases.

The di¤erence in expected employment between innovators and non-innovators

[13] The Cramer's V method measures the degree of association between the values of the row and column variables on a scale of 0 to 1, based on the usual chi-square statistic.

Table 2: Output and employment growth expectations for innovators and non-innovators

		expected increase between 1997-99							
		for university grad.				for masters/techn.			
	obs	means if y_j		CR	F	means if y_j		CR	F
y_j		= 0	= 1	V	½	= 0	= 1	V	½
product innov, (pd)	837	0:21	0:49	0:24	0:00	0:22	0:34	0:11	0:00
pd and process inno.	837	0:27	0:51	0:24	0:00	0:21	0:37	0:17	0:00
pd and cost-re. proc.	803	0:33	0:51	0:18	0:00	0:26	0:34	0:09	0:00
new prod., pos. rev.	729	0:27	0:50	0:22	0:00	0:22	0:35	0:14	0:00
new market prod.	768	0:33	0:57	0:25	0:00	0:26	0:39	0:14	0:00
exp. sales growth	837	0:24	0:52	0:28	0:00	0:20	0:36	0:18	0:00
patent application	733	0:33	0:57	0:25	0:00	0:29	0:32	0:04	0:34
		total employment				total sales			
	obs	means if y_j		CR	F	means if y_j		CR	F
y_j		= 0	= 1	V	½	= 0	= 1	V	½
product innov, (pd)	837	0:17	0:23	0:07	0:06	0:47	0:68	0:19	0:00
pd and process inno.	837	0:18	0:24	0:07	0:05	0:52	0:70	0:19	0:00
pd and cost-re. proc.	803	0:19	0:24	0:06	0:12	0:57	0:70	0:14	0:00
new prod., pos. rev	729	0:17	0:23	0:06	0:13	0:52	0:68	0:16	0:00
new market prod.	768	0:18	0:25	0:08	0:03	0:58	0:70	0:13	0:00
exp. sales growth	837	0:04	0:32	0:31	0:00				
patent application	733	0:21	0:22	0:01	0:79	0:59	0:70	0:11	0:00

Notes: West German …rms, Cr.V: Cramers V measures the degree of association between two dummy variables. F,½ : Probability(=marginal signi…cance level) of the two sided Fisher exact test which is used to test whether each dummy variable pair is independent.

Source: ZEW Mannheim Innovation Panel 1997, own calculations.

Table 3: Cross Table: R&D doing …rms and new market products

	obs	no new market products, 94-96	new market products, 94-96
R&D doing …rms: permament	343	0:33	0:67
R&D doing …rms: ocassional	172	0:60	0:40
non R&D doing …rms	59	0:81	0:19

Notes: West German …rms, restricted sample, observations 574. Non-innovators are excluded.

Source: ZEW Mannheim Innovation Panel 1997, own calculations.

can also be noticed for total employment. The di¤erence between these groups is, however, quite small and often not signi…cant at the 5 percent level, except for new market products with a 3 percent signi…cance level. Similar to university graduates, employment expectations for masters and technicans di¤er signi…cantly between innovators and non-innovators. For new market products 39 percent of the …rms plan to create new jobs for masters and technicans for the period of 1997 to 1999, compared to 22 percent for the non-innovative group. Not surprisingly, expected output change is a major determinant of job creation for all employment categories.

Cross-correlations in Table 3 con…rm that there is a positive relationship between R&D activities and the introduction of new market products. Moreover, the distinction between permament and occasional R&D activities is important. The highest proportion of new market product innovators (67 percent of all …rms based on restriced sample) can be found in …rms that are continuously engaged in R&D. For instance, …rms that are occasionally engaged in R&D are less likely to introduce new market products than …rms that are continuously engaged in R&D.

Before proceeding, several caveats regarding the sample should be noted. First, the sample reduction is quite large. Despite the drop in the estimation sample from 1330 to around 837 observations, most variables have a mean, that is very similar to the complete sample. One exception is the …rm size. Excluding …rms with no answers on important variables reduce the share of small …rms (size class 5-50) from 31.2 percent to 25.5 percent (see Table A2 in Appendix and Table A8 in Appendix). Second, to shed some light into the question whether the estimation sample is representative the sector distribution and the high-skilled employment share are compared between the Labour Force Survey and the …rm data. Machinery, rubber and plastics as well as precision instruments seem to be overrepresented.

4. Empirical results

4.1 Employment expectations and exogenous technological innovations

To assess the importance of technological innovations to job creation, firms expectations for different types of labour are examined. Different functions will be estimated for different types of innovations. We also include various interaction terms between different types of innovations.[14] We first start to estimate multivariate probit models explaining employment expectations for different types of labour, whereas technological innovations are assumed to be exogenous. For new market products this assumption will be relaxed in the following section. The dependent variables is whether or not firms plan to increase employment for employees with a university degree, for masters/technicans or for the total number of employees in the period between 1997 and 1999. Since regression results for different types of innovations indicate that the introduction of new market products (associated with positive sales gained from the new product) is more important than any other measure of product innovation in determining the expected employment probabilities, we first report the results using new market products. Furthermore, since the sample size reduction due to missing information on current sales growth rate is quite large, we substitute the expected output growth rate for the actual sales growth rate.

The top panel of Table 4 shows the results for the multivariate probit model estimated by simulated MLE. We use 200 replications for the GHK estimator. For the sake of comparison, the lower panel of Table 4 also includes simple univariate probit models for each employment group. Column 1 and 2 show the coefficients on the probability that firms expect an increase in university graduates and master/technicans, respectively. Column 3 shows the coefficient on the probability that firms expect an increase in total employment. All equations include 14 two-digit industry dummies. The reference group is machinery, NACE 291 and NACE 294. For the three equation multivariate probit models two out

[14] Separate employment functions are not estimated at the two-digit level because of the relatively small sample size in many cases. See Table A8 in Appendix for the sectoral breakdown.

of three correlation coefficients of the error terms are significantly positive at the 5 percent level. Not surprisingly, a Wald test clearly supports the seemingly unrelated probit model over the independent univariate probit model with a p-value of less than 0:01. The positive correlation coefficients indicate that firms expecting an increase for one employment group are also expecting an increase for the other employment group. Accounting for cross-correlation of the error terms should produce some efficiency gains. A comparison of the t-values of the multivariate probit model with the univariate probit model shows little evidence for efficiency gains which is somehow surprising.

Hajivassiliou (1997) shows that bias due to simulation noise decreases with the number of replications used for the GHK estimator.[15] The multivariate probit models are also estimated with different replications (R=300, R=400, R=500). Unreported results show that 100 replications are sufficient to stabilize both the log likelihood and the coefficients. However, for a small number of replications (R<50) the coefficients are quite different.

Table 4 shows that new market products enter significantly positive in all three employment expectation equations. For the employment expectations of university graduates and masters/technicans the coefficients on new market products are significant at the 1 percent level. For expected change in total employment, the coefficient on new market products is significant at the 8 percent level. Since the coefficients are similar for the SUR probit model with those for the univariate probit model, marginal effects from the univariate probit can be used to compare the employment effects of new market products. The marginal effects for university graduates, masters and technicians and total employement are 0:13, 0:12 and 0:05 respectively, indicating a higher magnitude for higher qualifications. This means that the average innovator is between 5 percent and 13 percent more likely to increase employment of different types of labour in the future.

Looking at the other coefficients, we see that all coefficients have the predicted signs. Expected employment growth for different types of labour is rather responsive to expected output growth. The estimated coefficient on the employment

[15] Haijvassiliou (1997) proposed a test for the bias generated by simulation noise in MSL estimation.

Table 4: Multivariate probit estimates for …rms' employment expectations

	university graduates		masters/ technicans		total employment	
	coe¤	t-stat	coe¤	t-stat	coe¤	t-stat
			multivariate probit:			
new market prod.	0:34	3:05	0:38	3:37	0:23	1:73
university grad. sh.	2:51	4:82				
masters/techn. share			1:20	2:34		
high-skilled share					0:60	1:62
expected sales	0:72	6:47	0:49	4:38	1:33	7:14
50 · L< 100	0:11	0:64	0:08	0:46	¡ 0:25	¡ 1:23
100 · L< 250	0:54	3:48	0:34	2:26	¡ 0:17	¡ 0:95
250 · L< 500	0:75	4:64	¡ 0:01	¡ 0:05	¡ 0:24	¡ 1:35
L ¸ 500	0:61	3:72	0:19	1:14	¡ 0:54	¡ 2:62
industry dummies	yes		yes		yes	
constant	¡ 1:19	¡ 5:35	¡ 1:11	¡ 5:17	¡ 1:77	¡ 6:44
$½_{1;2}$	0:43	7:17				
$½_{1;3}$	0:21	2:54				
$½_{2;3}$	0:04	0:01				
log-likelihood			¡ 1172:6			
			univariate probit:			
new market prod.	0:34	3:12	0:36	3:33	0:21	1:69
university grad. sh.	2:35	4:63				
masters/techn. sh.			1:27	2:67		
high-skilled share					0:62	1:82
expected sales	0:72	6:70	0:49	4:48	1:32	8:41
50 · L< 100	0:12	0:68	0:09	0:53	¡ 0:24	¡ 1:29
100 · L< 250	0:54	3:58	0:35	2:43	¡ 0:15	¡ 0:93
250 · L< 500	0:75	4:84	0:01	0:07	¡ 0:22	¡ 1:30
L ¸ 500	0:60	3:76	0:22	1:35	¡ 0:52	¡ 2:78
industry dummies	yes		yes		yes	
Constant	¡ 1:19	¡ 5:31	¡ 1:12	¡ 5:11	¡ 1:78	¡ 6:69
log-likelihood	¡ 432:2		¡ 437:0		¡ 330:5	

Notes: West German manufacturing …rms. Number of observations 768. Upper panel: multivariate probit model estimated by simulated MLE. Replications for simulated probabilities=200. Reference industry is Nace 291, 294.

share of university graduates and as well as that of masters and technicans are positive and significant at the 5 percent level. This is not very surprising, since employment growth is higher in industries that are intensive in human capital. Furthermore, job creation for university graduates is much more likely in medium sized firms ($100 - 249$ and $250 - 499$ employees) and in large sized firms than in both very small (up to 50) and small sized ($50 - 99$). In contrast, employment expectations for total employees are clearly negatively related to firm size. The highest employment expectations for masters and technicans can be found in the medium sized grouped.

The innovation effects may also be different for firms that introduce product and process innovations simultaneously compared to product innovations only. Therefore, a number of multivariate probit models are fitted including different measures of innovation. Table 5 shows the estimation results for the five different specifications. Specification (1) includes the broadly defined product innovation measure. Specification (2) includes the broadly defined product innovation measure and an interaction term between products and processes. Specifications (3) and (4) also include an interaction term between product innovation and the other two product innovation concepts. Specification (5) includes new market products and an interaction term between new market products and processes. Table 4 also includes a Wald test for joint significance of the innovation indicator and the interaction term.

The most important result is that new market products have stronger effects on the employment expectation probability than the other two product innovation measures. The coefficient on the interaction term of new market products and new or improved products is significant positive in each of the employment equations. Furthermore, a joint test reject the null hypothesis that both new and improved products and the interaction term are all equal to zero at the 5 percent level. The value of the test statistics ranges between 17.1 for the university graduates equation and 12.0 for the masters and technicans equation. The corresponding p-values are less than 0.01. In case of total employment both new products and the interaction term are not jointly significant at the 5 percent level. This indicates that based on the broader measure of product innovation

Table 5: Multivariate probit estimates for …rms' employment expectations

speci…cation		university graduates		masters/ technicans		total employment	
(obs)		coe¤.	t-stat	coe¤.	t-stat	coe¤.	t-stat
1	product inno.,(pd)	0:43	3:22	0:31	2:42	0:04	0:03
(837)	½$_{1;2}$; ½$_{1;3}$; ½$_{2;3}$ (t-st)	0:42(7:56); 0:21(2:65); 0:01(0:13)					
	Log-likelihood;obs.	¡ 1286:8					
2	product inno.,(pd)	0:27	1:45	¡ 0:11	¡ 0:56	¡ 0:10	¡ 0:51
(837)	pd£process inn.(pz)	0:19	1:21	0:49	2:77	0:12	0:75
	½$_{1;2}$; ½$_{1;3}$; ½$_{2;3}$ (t-st)	0:44(7:78); 0:20(2:51); ¡ 0:01(¡ 0:03)					
	Log-likelihood	¡ 1280:0					
	Wald test	13:4¤		15:4¤		0:60	
3	pd	0:39	2:59	0:15	0:92	¡ 0:11	¡ 0:65
(768)	pd£new market p.	0:20	1:62	0:33	2:56	0:26	1:82
	½$_{1;2}$; ½$_{1;3}$; ½$_{2;3}$ (t-st)	0:43(7:16); 0:22(2:61); 0:00(0:02)					
	Log-likelihood	¡ 1167:9					
	Wald test	17:1¤		12:0¤		3:3	
4	pd	0:47	2:22	¡ 0:10	¡ 0:43	¡ 0:07	¡ 0:28
(729)	pd£pos.rev	0:00	0:00	0:43	2:01	0:11	0:50
	½$_{1;2}$; ½$_{1;3}$; ½$_{2;3}$ (t-st)	0:42(6:60); 0:23(2:57); ¡ 0:01(¡ 0:05)					
	Log-likelihood	¡ 1086:2					
	Wald test	12:3¤		8:6¤		0:3	
5	new market product	0:26	1:15	¡ 0:12	¡ 0:42	0:39	1:60
(768)	new market£pz	0:08	0:36	0:57	2:05	¡ 0:20	¡ 0:79
	½$_{1;2}$; ½$_{1;3}$; ½$_{2;3}$ (t-st)	0:44(7:34); 0:21(2:52); 0:01(0:14)					
	Log-likelihood	¡ 1065:0					
	Wald test	9:9¤		16:4¤		3:4	

Notes: West German manufacturing …rms. Multivariate probit model estimated by simulated MLE. Replications for simulated probabilities=200. Reference industry is Nace 231, 294. Wald test for joint signi…cance of the innovation indicator and the interaction term with two degrees of freedom.

(new and improved products) the positive effect of innovation on employment expectations of the total number of employees disappears.

For university graduates as well as for the masters and technicans the positive interaction terms between product and process innovations suggest that joint implementation of new products and new processes have stronger effects than product innovations only. In contrast, for total employment, the interaction term between products and new processes is close to zero and not significant. Finally, unreported regression indicates that the combination of new products and cost reducing process innovations has similar effects on the employment probabilities.[16]

Some additional sensitivity checks are presented. The first point is that employment expectations may depend on the current employment growth rate. Reestimating each multivariate probit model with the current employment growth rate in 1996 as an additional right-hand variable shows that employment expectations depend positively on realised current employment growth rates. The coefficient on the current employment growth rate is significant for each type of labour. More important, the inclusion of past employment growth rates leaves the coefficient on new market product unchanged. However, due to missing information on lagged levels, the sample reduces to 547 observations, which means a loss of 23 percent. The second point concerns the simultaneity between expected sales growth and expected employment growth. This could lead to biased estimates of the expected sales coefficient. Moreover, expected employment change may be influenced by current sales growth rates rather than by its sales expectations. Similar to previous analyses, the inclusion of the current growth rate of sales leaves the coefficients on different innovation activities unchanged. The current growth rate of sales has a positive impact on the expected labour demand but is not significant at the 5 percent level. For instance, the coefficient on the current growth rate of sales in 1996 on the expected employment of university graduates is 0:24 with a t-value of 0:6. In contrast, the effects of the current growth rate of sales in 1996 on the expectations for the total employment is

[16] Furthermore, interaction terms between patents and product innovations are not significant.

signi…cantly positive.[17] Finally, the last point refers to heteroscedasticity. Modelling the variance of the error term as a function of R&D intensity, high-skilled employment share and its squared variables leaves the basic estimates unchanged. Not surprisingly, heteroscedasticity is rejected at the 5 percent level.

4.2 Accounting for endogeneity of new market products

Since non-innovative …rms are not compelled to answer all questions about innovation input we restricted the following analysis to innovative …rms, that are, …rms that either introduce product or process innovations. This only allows us to control for the possible endogeneity of new market products in the labour demand equations but not for the broader de…ned measures of innovation output. Excluding non-innovative …rms leads to an estimation sample of about 574 …rms. To account for endogeneity of new market products in the labour demand equations an innovation output selection equation is added to the system of equations. Table 6 shows the results for the baseline multivariate probit model which contains three di¤erent equations of employment expectation and one new market product equation. The innovation probit model identi…es factors in‡uencing the probability that the …rms introduce new market products during the period between 1994 and 1996. To compare the multivariate probit models assuming exogenous new market products with those that consider these as endogenous, we also show multivariate probit results assuming exogenous new market products (see Table A9 in Appendix). Again, for all speci…cations we use 200 replications for the GHK estimator. Di¤erent values for the number of replications indicate that the likelihood values have already stabilized using 100 replications.

Column 1 and 2 in Table 6 show the coe¢ cients on the probability that …rms expect an increase in university graduates and master/technicans, respectively. Column 3 shows the results for employment expectations for the total numbers of employees. Column 4 shows the coe¢ cients in‡uencing the probability that a …rm has introduced new market products between 1994 and 1996. The coe¢ -

[17] We also experimented with two-year growth rates of the total sales during the period between 1994 and 1996 rather than with the current growth rate. In this case the sample size is reduced to less than 400.

cients on 14 two digit industry dummies are not reported due to space limitations, but they are jointly signi…cant at the 5 percent level. Table 6 also includes the estimated correlation matrix for the four equations. The correlation coe¢cients of the error terms are signi…cant at the 5 percent level in two out of six cases. In general, the correlations are quite reasonable, with the highest correlation between the two skilled labour groups. However, the insigni…cant correlation coe¢cients between the errors in the employment equations and the new market products equation indicate that the new market product equation could be excluded from the model. In addition to the t-test on the correlation coe¢cients between the error terms in the employment expectation equation and in the new market product innovation equation, an exogeneity test can be performed. A Wald test is carried out for the null hypothesis H_0 : ½$_{n4}$ = 0; n=1,..3, against H_1 : ½$_{n4}$ 6= 0; n=1,..3. For the baseline speci…cation the chi squared test statistic is 2:4 and therefore considerably below the 5 percent critical value with 3 degrees of freedom.[18]

The inclusion of an innovation selection equation makes some di¤erence in the magnitude of the coe¢cients on new market products in the labour demand equations. Since the exogeneity assumption of new market products can not be rejected, separate estimates for the system of employment equations and the innovation equation are more e¢cient. Therefore, the interpretation of the coef…cients in the labour demand equations should be based on the three equation multivariate probit model and the univariate probit model for the innovation equation (see Table A9 in Appendix). Column 4 shows the coe¢cients in‡uencing the probability that a …rm has introduced new market products between 1994 and 1996. The signi…cantly positive coe¢cient on the R&D dummy variable de…ned as whether or not …rms are continuously engaged in R&D, indicates that the probability to innovate depends on the …rms' R&D activity. Furthermore, the second R&D dummy variable de…ned as whether or not …rms are occasionally engaged in R&D is also sign…cantly positive at the 5 percent level. The posi-

[18] I also estimated bivariate probit models for each pairs of employment expectation and new market products. In general, the null hypothesis of exogeneity of new market products can not be rejected at the 5 percent level.

tive relationship between innovation output and R&D has also been found by most previous studies (see for example Brouwer and Kleinknecht (1996) based on Dutch manufacturing …rms). The high-skilled employment share and the dummy variable for subsidies are both positive but not signi…cant at the 5 percent level. Furthermore, the introduction of new market products depends signi…cantly positively on …rms size. The coe¢cients on the …rm size dummies, however, should be interpreted with caution. One reason for the positive relationship between the innovation probability and the …rm size is that in small …rms product innovation is incremental, so the discrete innovation variable will underestimate the level of innovative activity (see Roper (1997)). Large …rms are more likely to be successful innovators.

Furthermore, as can be seen in Table A9 in Appendix, the results are quite similar to those reported in Table 4 based on the full sample. There is again a strong positive correlation between the successful introduction of new market products during the period between 1994 and 1996 and the probability to increase employment in the future period between 1997 and 1999. However, the coe¢cient on new market products in the university graduates equation is only signi…cant at the 10 percent level.

In unreported regressions, we experimented with alternative measures of innovation input. The …rst alternative measure is the R&D intensity and the second the innovation sales ratio. The results for the exogeneity tests based on the additional speci…cations are presented in Table 7. This table also includes the exogeneity test for the baseline speci…cation in Table 6. The Wald tests suggest that endogeneity of new market products is important for the alternative measures of innovation inputs such as the R&D intensity as well as the innovation sales ratio. Given the values of the Wald test statistics for speci…cation (ii) and (iii) the null hypothesis of exogeneity of new market products, $H_0 : ½_{14} = ½_{24} = ½_{34} = 0$; can be clearly rejected at the 1 percent level. Moreover, when controlling for endogeneity an insigni…cant relationship between new market products and the employment expectations for both university graduates

Table 6: Multivariate probit estimates: expected employment growth and introduction of new market products

	expected change 1997-99						new market	
	university		masters and		total		product	
	graduates		technicans		employment		1994-96	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
new market pr.	0.11	0.21	0.01	0.03	0.87	1.86		
univ. grad sh.	2.29	3.68						
masters sh.			1.30	2.03				
high-skilled sh.					0.63	1.37	0.43	1.20
exp. sales	0.74	5.39	0.51	3.75	1.16	4.22		
R&D continuous							0.97	4.02
R&D occasional							0.40	1.67
subsidies							0.20	1.24
sales sh. pr. 1							−0.09	−0.34
$50 \le L < 100$	0.11	0.52	0.09	0.45	−0.30	−1.33	−0.12	−0.55
$100 \le L < 250$	0.39	2.02	0.33	1.72	−0.41	−1.91	−0.12	−0.63
$250 \le L < 500$	0.69	3.20	0.06	0.26	−0.52	−2.40	0.34	1.75
$L \ge 500$	0.57	2.60	0.25	1.09	−0.82	−3.41	0.41	2.06
industry d.	yes		yes		yes		yes	
Constant	−1.40	−6.15	−0.90	−2.78	−1.81	−5.80	−0.49	−2.08
$\rho_{1,2}$	0.47	6.21						
$\rho_{1,3}$	0.22	1.68						
$\rho_{2,3}$	−0.03	−0.23						
$\rho_{1,4}$	0.06	0.19						
$\rho_{2,4}$	0.20	0.69						
$\rho_{3,4}$	−0.41	−1.31						
Log-L					−1257.6			

Notes: West German manufacturing firms. Number of observations 574. Replications for simulated probabilities=200.

Table 7: Wald test of exogeneity of new market products

speci…cation: measures of innovation input	test statistic	p-value
(i) R&D dummies (continuously , occasionally)	2:37	:50
(ii) R&D intensity	32:4	:00
(iii) innovation sales ratio	63:3	:00

Notes: Wald test of the Exogeneity assumption is based on : H_0 : ½$_{14}$ = ½$_{34}$ = ½$_{34}$ = 0: The number of degrees of freedom is 3. Number of observations 574.

and masters and technicans arises which is somehow surprising.[19]

However, the interpretation of the results based on the R&D intensity as measure of innovation input should be interpreted with caution. Innovation output as a function of R&D intensity can be criticized because of the possible adjustment lags between innovation output and R&D investment as well as simultaneity. Since R&D dummy variables based on the question whether or not …rms are continuously or occasionally engaged in R&D do not refer to a speci…c time period, the simultaneity problem between R&D and innovation output can be avoided.

Another point refers to the speci…cation of the innovation equation. According to the demand-pull hypothesis, …rms' prospects regarding future sales could affect their innovation activities (see Brouwer and Kleinknecht (1996)). Including expected sales growth as an additional regressor in the innovation equation leaves the basic results unchanged. The coe¢cient on expected sales is very small and not signi…cant at the 5 percent signi…cance level.

[19] Results for the multivariate probit model that contains R&D intensity instead of a R&D dummy is available on request.

5. Conclusions

The paper deals with the relation between technological innovations and the firms' present expectations for future employment. A multivariate probit model explaining employment expectations for different types of labour is estimated using simulated ML methods. Special attention is directed to the measurement of innovation as well as the potential endogeneity of innovation output in the expected employment equations. The main findings of this analysis are the following: Firms that introduced new market products in the past are more likely to plan increased employment in the future. More important, the employment effects of new market products have a higher magnitude for higher educational qualifications. For total employment the results suggest that the introduction of new market products is more important than any other measure of product innovation in determining job creation. For instance there are no positive total employment effects when innovation is measured either as the introduction of new and improved products or as a combination of product and process innovations. In contrast, for both university graduates and masters and technicans employment effects of joint implementation of new products and new processes are stronger than the introduction of new and improved products not combined with new processes. Labour quality and expected turnover are also important determinants of expected labour demand.

Concerning possible endogeneity of new market products in the labour demand equations, the exogeneity assumption of new market products can not be rejected at conventional significance levels. Estimation results for the innovation equation indicate that the probability whether or not new market products are introduced is significantly higher for firms that are continuously engaged in R&D.

Appendix: Descriptive statistics

Table A1: Questionnaire and generated variables

original questionnaire	
employment, L	number of employees and by educational qualificat., end 96
sales	total turnover in 1994, 1995 and 1996
expected performance	firms expectations for output, employment by education, during the three year period, 97-99, orderd categorical var.
product inno. (pd)	Between 1994-96 has your enterprise introduced any technologically new or improved products? (yes/no)
process inno. (pz)	Between 1994-96 has your enterprise introduced any technologically new or improved processes? (yes/no)
cost-red pz inno.	cost reduction due to the introduction of technologically new or improved process in percent
new product sales share	turnover in 1996 due to techn. new or considerably improved products to your enterprise introduced between 94-96, percent
new/improved product sales s.	turnover in 1996 due to techn. new or improved product enterprise introduced between 1994 and 1996 in percent
new market product	Between 1994 and 1996 did your enterprise introduce technologically new or improved products not to your enterprise but also to your market?
new market pr. sales sh.	turnover in 1996 due to new market products introduced between 1994 and 1996 in percent
patent	Did your enterprise apply for at least one patent between 1995 and 1997 in any country?
sales sh prod 1	Sales share of the product most intensive in sales? (percent)
subsidy	Did your enterprise receive any government support for innovation activities in 1996? (loans incl. a subsidy element)
R&D	Did your enterprise engage in R&D? (i) Continously, (ii) occasionally, (iii) not at all.
R&D intensity	Share of R&D expenditures (incl. labour costs of R&D staff, acquisition of services and capital expenditures) in sales, 96
Innovation inten.	Innovation expenditure sales ratio, 1996 in percent

Source: Janz and Licht (1999), ZEW Mannheim Innovation Panel 1997 .

Continued Table A1:

generated variables	
expected performance, 1997-99, (increase=1, unchanged/decrease=0):	
ex. sales	expected sales growth
ex. employment	expected employment growth
ex. univers. grad.	ex. university graduates employment growth
ex. masters/tech.	ex. masters/technicans employment growth
other (0/1 variables):	
cost-red process	cost reduction equals 1, 0 else
new product	positive new products sales in 96=1, 0 else
university grad.	university graduates in percent of the sum of all educational quali…cation groups in 96
masters share	masters and technicans in percent of the sum of all educational qual. groups, 96
high-skilled sh.	university graduates incl. masters/tech. in percent of the sum of all educational qual. groups, 96
labour product.	total sales per total number of employees in 1996
industry dummies	1,...,17 manufacturing industries in 1996
size dummies	1,...,5 size classes in 1996
¢y	growth rate for total sales in 1996
¢l^a	growth rate for total number of employees in 1996
¢l^h	growth rate for university graduates in 1996
¢l^m	growth rate for masters/technicans in 1996

Table A2: Means of variables, total sample

	obs.	means	median	variable
total sales	1396	173	32	contin.
university grad., engineers, natural sc., 96	1258	34	4	cens.
university grad., social science, 96	1233	13	1	cens.
higher tech. college deg., white collar, 96	1226	29	5	cens.
vocational college degree, white collar, 96	1236	121	32	cens.
other employees (incl. blue collar), 96	1207	182	32	cens.
		in percent		
university graduates employ. sh., 96	1177	9:0	4:8	cens.
university graduates employ. sh., 95	1036	8:2	4:4	cens.
master, technicians employ. sh., 96	1177	8:8	5:3	cens.
master, technicians employ. sh., 95	1036	8:3	4:7	cens.
ex. sales growth, 97-99	1371	58:9		0=1
ex. employment growth, 97-99	1371	20:7		0=1
ex. university graduates, 97-99	1166	44:6		0=1
ex. master/technicans, 97-99	1240	31:6		0=1
product innovation, 94-96	1397	69:8		0=1
process innovation, 94-96	1397	60:0		0=1
pd and process innov., 94-96	1397	57:2		0=1
pd and cost-red.process inn., 94-96	1311	44:9		0=1
new market products, 94-96	1228	39:2		0=1
pd and pos. new prod. rev, 94-96	1148	55:7		0=1
turnover sh.due to new/improved p., 96	1082	31:1	25	cens:
turnover sh. due to new prod., 96	1082	14:0		cens:
turnover sh. due to new market p., 96	1058	3:9	0	cens:
R&D intensity in 96	1358	1:7	0:2	cens:
continuous R&D activities	1329	49:6		0=1
occasional R&D activities	1329	21:0		0=1
subsidies in 96	1313	15:3		0=1
sales share product 1	1286	62:2	60	cens:
5 · L < 50	1397	31:2		0=1
50 · L < 100	1397	13:7		0=1
100 · L < 250	1397	19:1		0=1
250 · L < 500	1397	16:5		0=1
L ¸ 500	1387	18:7		0=1

West German manufacturing. Firms with 4 or less employees are excluded.

Source: ZEW Mannheim Innovation Panel 1997, own calculations.

Table A3: Firms' expectations for sales and employment (percent)

	expected performance 1997-99				
	total	employ-	high-skilled labour		
	sales	ment	engineers/ nat. sc.	social sciences	master/ technicans
strong decrease	4:1	7:8	1:2	0:8	1:2
weak decrease	9:4	26:1	2:4	4:2	5:3
unchanged	23:4	44:8	59:4	77:7	62:7
weak increase	53:6	20:2	33:0	16:1	29:0
strong increase	9:4	1:2	4:1	1:2	1:8

West German manufacturing …rms, observations; 837.

Source: ZEW Mannheim Innovation Panel 1997, own calculations.

Table A4: Employment expectations for university graduates by degree group

engineering/ natural science (rows)	social and other sciences decrease	unchanged	increase	Total
	cases (percent in parenthesis)			
total sample (obs=1132)				
decrease	33 (2:9)	12 (1:1)	1 (0:1)	46 (4:1)
unchanged	16 (1:4)	590 (52:1)	59 (5:2)	665 (58:7)
increase	17 (1:5)	257 (22:7)	147 (13:0)	421 (37:2)
Total	66 (5:8)	859 (75:9)	207 (18:3)	1132 (100)
estimation sample (obs=837)				
decrease	20(2:4)	9 (1:1)	1 (0:1)	30 (3:6)
unchanged	12 (1:4)	446 (53:3)	39 (4:7)	497 (59:4)
increase	10 (1:2)	195 (23:3)	105 (12:5)	310 (37:0)
Total	42 (5:9)	650 (77:7)	145 (17:3)	837 (100)

West German manufacturing …rms.

Source: ZEW-Mannheim Innovation Panel 1997, own calculations.

Table A5: Educational quali…cation structure in manufacturing

educational quali…cations:	numbers 91	93	95	annualized growth rates 95/91	quali…cation structure 91	93	95
	in 1000s			percent	percent		
without any degree/ apprenticies	2113	1852	1535	¡ 6:2	18:4	16:7	15:9
vocational school	5933	5585	4908	¡ 3:7	61:2	61:2	61:4
master/technicans	979	949	847	¡ 2:9	10:1	10:4	10:6
univer./polytech deg.	378	392	384	0:3	3:9	4:3	4:8
university degree	310	338	312	0:1	3:2	3:7	3:9
total employment	9694	9125	7993	¡ 3:8	100	100	100

[a]West German manufacturing. Including self-employees.

Source: Micro Census, 70 percent sample, own calculations.

Table A6: Output and employment growth in manufacturing (percent)

year	manuf. value added growth	employment growth: national accounts	employment growth: social security stat.	employ. growth by education: university grad.	vocational school	without any degree
90	5:5	2:8	2:8	4:4	4:1	¡ 0:2
91	3:7	1:4	0:9	4:5	2:1	¡ 2:4
92	¡ 2:7	¡ 1:9	¡ 3:1	2:1	¡ 1:4	¡ 7:4
93	¡ 8:2	¡ 6:3	¡ 6:4	¡ 2:2	¡ 4:8	¡ 10:7
94	1:8	¡ 5:4	¡ 4:0	¡ 1:1	¡ 3:0	¡ 7:1
95	0:2	¡ 2:3	¡ 2:2	1:6	¡ 1:6	¡ 4:8
96	¡ 1:3	¡ 3:3	¡ 3:1	2:2	¡ 2:6	¡ 6:1
97	3:6	¡ 2:4	¡ 1:7	3:4	¡ 1:5	¡ 2:7
98	5:2	¡ 0:2	¡ 0:2	2:8	¡ 0:4	¡ 1:0

West German manufacturing. Source: Federal statistical o¢ce. GDP: http://194.95.119.6/zeitreih/dok/sgu1496.htm;

Employment by educational quali…cation only covers workers paying social security contributions: http://194.95.119.6/zeitreih/dok/sgz2197.htm, own calculations.

Table A7: Distribution of degree (percent)

Labour Force Survey (micro census), April 1995		MIP 1997	
engineering (mechanical, electro engineering)	51:4	engin./	
natural science (chemists, physics, biologist, computer)	24:4	nat. sc	73:0
other degree (social science, business, law, arts)	24:2	other sc.	27:0

[a]West German manufacturing based on 1221 observations.

Source: Micro Census, 70 percent sample, own calculations.

Table A8: High-skilled employment shares by sector

nace 3-digit	sector	Labour Force Survey 95: total employment (1000s)	Labour Force Survey 95: high-skilled sh. university grad.	Labour Force Survey 95: high-skilled sh. univer./ master/ techn.	MIP 5th wave, 97: high-skilled sh. university grad.	MIP 5th wave, 97: high-skilled sh. univer./ master/ techn.	cas-es
			in percent				
151-160	food	718	3:8	14:8	6:9	13:7	43
171-193	textile	429	4:2	10:0	4:8	13:9	41
201-223	wood,paper	972	6:5	15:2	4:7	12:2	63
231-247	chemicals	643	14:7	24:1	13:7	21:9	71
251-252	plastics, rubber	297	4:8	11:7	6:1	12:5	78
261-268	glass, minerals	247	5:6	13:5	5:0	11:1	45
271-275	basic metals	476	5:7	14:8	4:0	10:4	27
281-287	metal products	891	4:7	13:9	7:0	15:0	93
291,294	machinery	426	12:2	25:2	9:9	19:4	60
293,295-97	other machinery	463	12:7	24:9	13:6	24:9	56
292	o. purpose mach.	188	12:4	24:3	13:8	24:9	61
300,321-23	comput., comm.	319	24:6	36:8	19:3	31:0	28
311-316	electrical equip.	467	16:7	25:1	12:2	20:3	40
331-335	precision instr.	247	11:1	27:5	19:3	32:0	58
340-343	motor vehicles	720	10:0	20:6	10:2	16:0	21
351-355	transport equip.	128	13:5	26:4	13:6	20:2	17
361-372	Misscan.	324	3:5	12:6	4:0	12:3	35

Notes: Firm observations for 1996 university graduates employment shares are 837.

Source: ZEW Mannheim Innovation Panel 1997, own calculations.

Table A9: Multivariate probit estimates for …rms' employment expectations (restricted sample) and univariate probit model for …rms' new market product decision

	multivariate probit model						univ. probit	
	university graduates		masters/ technicans		total employment		new market products	
	coe¤	t-stat	coe¤	t-stat	coe¤	t-stat	coe¤	t-stat
new market pr.	0:20	1:60	0:33	2:53	0:25	1:69		
univ. grad. sh.	2:26	3:92						
mast./tech. sh.			1:27	2:06				
high-skilled sh.					0:84	2:10	0:42	1:21
expected sales	0:73	5:63	0:50	3:72	1:27	5:69		
R&D continuo.							1:07	4:84
R&D occasion.							0:48	2:16
subsidies							0:16	1:13
sales sh. pr. 1							¡ 0:10	¡ 0:40
50 · L< 100	0:11	0:52	0:08	0:40	¡ 0:31	¡ 1:34	¡ 0:09	¡ 0:43
100 · L< 250	0:38	2:06	0:33	1:84	¡ 0:42	¡ 1:99	¡ 0:12	¡ 0:66
250 · L< 500	0:67	3:59	¡ 0:01	¡ 0:04	¡ 0:40	¡ 1:94	0:32	1:74
L ¸ 500	0:56	3:04	0:17	0:90	¡ 0:67	¡ 2:62	0:40	2:10
ind. dummies	yes		yes		yes			
constant	¡ 1:01	¡ 3:81	¡ 1:05	¡ 4:32	¡ 1:66	¡ 5:28	¡ 0:74	¡ 2:41
$½_{1;2}$	0:45	6:67						
$½_{1;3}$	0:24	2:54						
$½_{2;3}$	0:01	0:15						
log-likelihood			¡ 923:0				¡ 336:7	

Notes: West German manufacturing …rms. Multivariate probit model estimated by simulated MLE. Replications for simulated probabilities=200. Reference industry is Nace 291, 294.

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