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Employment Changes in Environmentally Innovative Firms

Klaus Rennings, Andreas Ziegler and Thomas Zwick

ZEW

Zentrum für Europäische Wirtschaftsforschung GmbH

Centre for European Economic Research

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Non-technical summary

In the scientific and political debate increasing attention is drawn to the question of how ecological transformation towards cleaner production affects the economic performance of industries, especially concerning employment. Views about the direction of these impacts are highly controversial. From a micro-economic perspective, it is often argued that increasing ecological efficiency strengthens economic competitiveness and thus environmentally oriented innovations will become a key strategic factor for the profitability of firms. A popular hypothesis is that lower inputs of natural resources in the production process due to improved eco-efficiency require higher labour inputs and thus lead to positive employment effects. However, this position is contradicted by observations over the past decades that innovations improve both energy and labour productivity and therefore replace labour.

In theoretical papers and simulations with macro-economic models the impacts of cleaner production, i.e. the shift from end-of-pipe to integrated technologies, on employment are still controversial. The empirical investigations on the firm level usually show that product innovations have a small positive while process innovations have a negative or insignificant positive impact on employment. These studies frequently suffer from selection bias and measurement errors, however. Our paper overcomes these estimation problems by using tendency data and concentrating on the employment changes of innovative firms that have been identified to stem directly from the innovation. It analyses the determinants of employment reactions induced by environmental innovations using data from more than 1500 firms that have introduced environmental innovations in five European countries recently (Germany, United Kingdom, Italy, Netherlands, Switzerland). In an earlier paper the popular Multinomial Logit Model was used for the analysis of these data. In this paper, in order to check the robustness of our results, we compare various discrete choice models. The Multinomial Logit Model is restrictive, because it has the so-called "independence of irrelevant alternatives" property, which can be avoided by estimating Multinomial Probit Models. While the Multinomial Independent Probit Model is still restrictive because of the independence assumption in the stochastic components, the Flexible Multinomial Probit Model provides the most general discrete choice framework since it allows for correlations between all alternatives of the endogenous variable. We encounter identification problems in these estimations, however, due to the structure of our explanatory variables.

We find that most results of our earlier analysis are robust with respect to the specification of the discrete choice model. Environmental

product and service innovations increase significantly the probability of creating jobs and therefore support also labour market goals. In contrast to this, end-of-pipe eco-innovations increase the risk of destroying jobs, however at a higher significance level. Environmental innovations are skill-biased, they have a significant impact on employment changes if they are substantial and if they are induced by regulations. Firms expecting increasing sales are more prone to increase employment, while firms that want to slash costs by innovation and compete by soft factors decrease employment more frequently. Only the impact of the control variable firm size on employment reactions becomes insignificant by using the Flexible Multinomial Probit Model.

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KLAUS RENNINGS, ANDREAS ZIEGLER, AND THOMAS ZWICK

CENTRE FOR EUROPEAN ECONOMIC RESEARCH (ZEW)

P.O. BOX 103443, D-68034 MANNHEIM, GERMANY

TEL. ++49-0621-1235207, FAX: ++49-0621-1235225

EMAIL: rennings@zew.de, ziegler@zew.de, zwick@zew.de

Abstract

This paper analyses the determinants of employment reactions induced by environmental innovations. On the basis of the parameter estimates of the Multinomial Logit and of several Multinomial Probit Models, we show that we have to distinguish between the factors that have an impact on employment increases and employment decreases. The data stem from a telephone survey covering about 1600 firms in five European countries that introduced eco-innovations recently. Environmental product and service innovations increase significantly the probability of creating jobs. Thus, supporting these innovations does not counteract labour market policy. In contrast to this, end-of-pipe eco-innovations increase the risk of destroying jobs, however at a higher significance level. Environmental innovations are skill-biased, they have a significant impact on employment changes if they are substantial and if they are induced by regulations. Firms expecting increasing sales are more prone to increase employment, while firms that want to slash costs by innovation and compete by soft factors decrease employment more frequently.

Key Words: Innovation, labour demand, discrete choice models

JEL classification: C 25, J 23, O 33

1. Introduction

The existing microeconometric evidence on the relation between technological progress and employment on the firm level mainly concentrates on the differences in the employment development between innovating and non-innovating firms (see Brouwer et al., 1993, König et al., 1995, van Reenen, 1997, Rottmann and Ruschinski, 1998, Spiezia and Vivarelli, 2000, and Pfeiffer and Rennings, 2001). This literature shows that innovative firms enjoy a better employment record. In addition it is found that product innovations have a positive impact on employment since they create new demand, while process innovations increase the productivity of firms and have a negative or insignificant positive impact on employment. Therefore, the results seem to be unequivocal although most studies suffer from possible spurious correlation effects because third unobserved factors like management skills may influence the decision to introduce innovations as well as the employment development. Therefore, the cross-sectional estimations possibly suffer from selection bias (see Spiezia and Vivarelli, 2000). The rare true panel studies (see e.g. Rottmann and Ruschinski, 1998) minimize this possibility, however.

The conventional approach of the studies mentioned above is comparing the employment development of innovating and non-innovating firms or estimating a labour demand function including innovation dummies. The scope of this paper is more modest: Instead of calculating the number of jobs created or lost by certain innovations, it concentrates on the factors that have an impact on the propensity of the firms to change their number of employees due to an environmental innovation. Using tendency data of the firm's employment decision reduces the likelihood of measurement error (see Zimmermann, 1991). In addition, by concentrating on innovating firms only, we avoid biased estimations due to self-selectivity. Finally, we have data on the direct employment impact induced by the eco-innovation instead of aggregated employment changes that are influenced by a wealth of different factors. Thus we avoid measurement errors induced by the use of general employment development as an instrument for the direct employment effect of an innovation. It seems reasonable that the influencing factors for an increase differ from those to keep the employment constant or decreasing it and therefore we analyse discrete choice models with the three alternatives of the employment reactions. Our data stem from a telephone interview conducted in five European countries and covering about 1600 firms. The firms were interviewed only if they had introduced an environmental innovation between 1998 and 2000. Therefore we concentrate on this kind of innovation and take account of its peculiarities. The data set provides a broad variety of relevant explanatory variables.

Methodically, in order to check the robustness of our results, we compare various discrete choice models. In a first step we estimate the popular Multinomial Logit Model. This model is restrictive, because it has the so-called "independence of irrelevant alternatives" property, which can be avoided by estimating Multinomial Probit Models. While the Multinomial Independent Probit Model is still restrictive because of the independence assumption in the stochastic components, the Flexible Multinomial Probit Model provides the most general discrete choice framework since it allows correlations between all alternatives of the endogenous variable. We encounter identification problems in these estimations, however, due to the structure of our explanatory variables.

The paper is structured as follows. In section 2, we present our conceptual approach, including basic definitions and hypotheses. Section 3 presents the data and the variables used. Section 4 analyses the determinants of the employment tendency in the wake of environmental innovations while last section draws some conclusions.

2. Conceptual approach

Environmental innovations consist of new or modified processes, techniques, practices, systems and products to avoid or reduce environmental damage. Environmental innovations may be developed with or without the explicit aim of reducing environmental damage. They also may be motivated by the usual business goals such as reducing costs or enhancing product quality. Many environmental innovations combine an environmental benefit with a benefit for the company or user (see also Hemmelskamp, 1997, Rennings, 2000).

We assume a two-stage decision process of the firm. It decides first on the resources to invest in innovation and, depending on the outcome, determines at a second stage the profit-maximizing volume of labour input (see also König et al., 1995, Rottmann and Ruschinski, 1998). Our study concerns the second-stage employment decision for a given successful innovation. Several key factors have to be taken into account as an explanation for the employment impact of technological change: the type of eco-innovation, the innovation goal, the size of the innovation, the competitive environment, demand effects, environmental regulations, and sectoral as well as firm size effects (see also Rottmann and Ruschinski, 1998, Pianta, 2000).

According to the OECD Oslo Manual (OECD, 1997), we distinguish between (environmental) technical and organisational innovations. Technical innovations are further subdivided into integrated and end-of-pipe innovations. Integrated innovations include product, service and integrated process innovations. Recycling can not easily be subsumed under these categories. Process-internal recycling can be understood as cleaner technology while process-external recycling is an end-of-pipe technology. To avoid any confusion, it is reasonable to treat recycling as a separate category. Logistics, product delivery and distribution systems are also introduced as one separate innovation category. This is motivated by their increasing importance and because not all firms may understand these activities as process innovations.

According to the empirical literature, we expect that product and service innovations have a positive while integrated process and logistics innovations have a negative direct employment effect. Environmentally friendly process innovations do not necessarily increase the productivity of a firm, however. They may even reduce productivity and require increasing labour inputs per unit because they are often not motivated by cost reduction or increasing sales, but by compliance with environmental regulation (see Cleff and Rennings, 1999) and therefore, their net effect is unclear. We assume that end-of-pipe and recycling measures tend to have positive direct employment effects. They create new steps and links in the value chain and thus have a potential for additional employment. Organisational measures are initially accompanied by additional expenditure and work processes (e.g. undergoing an eco-audit procedure), which may also create positive direct employment effects.

The three most frequently mentioned reasons for introducing the innovation are an improvement of the firm’s image, to comply with environmental regulation and to reduce costs. The innovation goal “increasing the market share” plays only a minor role for introducing eco-innovations. The goals associated with an innovation may differ between firms of the same innovation category. It can be expected that cost reduction targets have a negative impact. When the innovation was introduced in order to increase market share, this should have a positive influence on employment, while the sign of the other reasons is unclear.

Since employment changes only occur when the labour turn-over costs are more than compensated (see Rottmann and Ruschinski, 1998), it can be expected that only major innovations have an impact on employment. The same should apply if the innovation was induced by environmental regulation because regulations may have a large impact on the firm´s structure. Finally, firms with optimistic sales ex pectations should be more inclined to increase employment already before demand actually increases. This is the well-known demand pull hypothesis of innovations (see e.g. Rottmann and Ruschinski, 1998, Pianta, 2000).

The competitive environment may also have an impact on the employment effect of innovations. Firms competing on the basis of costs probably display a different employment behaviour than firms competing on innovativeness, quality, or environmental performance. In this study, we discern between the hard competition factors price and quality and soft competition factors corporate image or innovativeness as the main sources of competition. For the hard competition factors the employment reactions depend on the relative importance of costs with respect to quality and the impact of the soft factors may also be in both directions a-priori.

Innovations always induce training needs. Usually better trained employees are more flexible and efficient in acquiring new skills and therefore they are in a better position to take advantage of innovations (see Muysken and Zwick, 2000). A high share of highly qualified employees is therefore probably necessary for a successful and employment enhancing implementation of an innovation and therefore skill biased technological change is observed (see van Reenen, 1997).

Firm size, country, and sector dummies are included in order to control for heterogeneity between countries, sectors, and smaller and larger firms. Wage changes that may also have an impact on employment changes induced by innovations are not included in the data set. We therefore have to assume that differences in labour costs are captured by the sector and firm size dummies. In addition, wage changes frequently have insignificant impacts in employment change regressions (see Pianta, 2000).

3. Description of the variables

3.1. Data and the dependent variable

In this paper, we analyse data from the IMPRESS project (acronym for: The Impact of Clean Production on Employment – A Study using Case Studies and Surveys, see Rennings and Zwick, 2001, for further details). In spring 2000, 1594 telephone interviews with industry and service firms were conducted in five European countries (401 from Germany, 384 from Italy, 201 from Switzerland, 400 from the United Kingdom, 208 from the Netherlands). The addresses for the interviews were drawn from a stratified representative sample with the dimen sions small firms (between 50 and 199 employees) and large firms (200 or more employees) and 8 sectors according to the NACE codes D-K. These NACE codes are industry, manufacturing and services. Firms active in other sectors such as mining, agriculture, the health sector or public administration are not included in the sample. The firms contacted were asked first if they had introduced at least one eco-innovation from the types discussed in section 2 during the last three years. If this was not the case, the interview was terminated.

We use a stratified representative sample considering the cells mentioned above. The results of the survey are therefore representative for eco-innovators in each country under the assumption that eco-innovators do not differ in their characteristics from other firms. Since this is a very restrictive assumption, the survey results should not be interpreted as being representative for all eco-innovators. A representative survey of eco-innovators can only be carried out if the universe of eco-innovating firms is known, which is not the case. All firms which had introduced eco-innovations were asked if these innovations increased, decreased or had no noticeable effect on the number of long-term employees which are the three categories of our discrete dependent variable "employment reaction". 88% of the firms stated that the realized environmental innovations had no noticeable employment effect. 9% of the firms reported an increase and 3% of the firms stated a decrease of the employment, induced by eco-innovations.

Thus, in the econometric analysis we do not use the overall employment change in the firm as a proxy for the employment change induced by the innovation like most comparable studies in the literature, because external economic effects and unobserved heterogeneity of the firms may induce measurement errors. The firms were also asked about the overall employment development in the same period, though. We find large differences between total employment change and employment reactions attributed to the eco-innovation and interpret this as an indication that the managers were able to differentiate between both.

3.2. Explanatory variables

The questionnaire provides a wide range of possible variables that help to test the hypotheses derived in section 2. In preliminary Logit and Probit estimations, these variables were tested on their explanatory power. Those were excluded whose parameters were consistently insignificant different from zero (significance level 5%). We therefore excluded the dummy variables of some countries and all sector variables, and the dummy variables of organisational, logistic and process integrated innovations. Thus contrary to the expectations in section 2 we can not validate any employment reactions by these three types of eco-innovations. Explanatory variables in the discrete choice analysis are therefore the other environmental innovations. The dummy variables PRODUCT-INN, SERVICE-INN, RECYCLING-INN, and END-OF-PIPE-INN take the value one if the enterprise introduces an ecological product, service, recycling or end-of-pipe innovation.

While the variance covariance matrix of the list of eco-innovations did not allow a reduction of variables by a factor analysis, this was possible for the list of innovation goals and the main competition factors (see Rennings and Zwick, 2001, for details). From the list of seven innovation goals the factor analysis extracted three independent factors. The variables “comply to environmental regulations”, “achieve an accreditation” and “improve firm´s image” were named ENVIRONMENTAL-FACTORS, “secure existing markets”, “increase market share” and “respond to competitor´s innovation” were named MARKET-SHARE, and “reduce costs” was a factor of its own (named COST-REDUCTION). For the competition situation, two independent factors could be identified. Price and quality were combined to “hard“ competition factors (named HARD) while corporate image, environmentally friendly features and innovative products and services were combined to “soft” factors (named SOFT). Notice that the factor HARD loads negatively with the underlying variables.

Table 1: Mean of the explanatory variables

VARIABLE	Number of observations	Mean
PRODUCT-INN	1592	0.174
SERVICE-INN	1591	0.118
RECYCLING-INN	1592	0.318
END-OF-PIPE-INN	1592	0.318
LARGE	1594	0.245
EXPENDITURE-SHARE	1284	0.181
UNIVERSITY	1321	0.187
SALES-EXP	1482	0.789
REGULATION	1566	0.534
GERMANY	1594	0.252
Net Sample	1040	

Source: IMPRESS Questionnaire, April 2000, own calculations.

The dummy variables LARGE and EXPENDITURE-SHARE take the value one if the firm has more than 200 employees and if the share of the relevant environmental innovation has a share larger than 25% of total innovation expenditures. The variable UNIVERSITY indicates the share of employees with a college or university degree (in percent/100). The dummy variables SALES-EXP, REGULATION and GERMANY are one, if the enterprise expects a rise in revenues, if the environmental innovation was induced by environmental regulations and if the firm is situated in Germany. In Table 1 the average shares of the explanatory variables are displayed.

4. Econometric analysis

4.1. Discrete choice models

We assume that the firm i (i=1,...,1040) as a result of the realized eco-innovation has to choose one of the mutually exclusive alternatives: to hire employees (alternative j=1), to fire employees (alternative j=2) or to make no change in the employment (alternative j=3). The underlying latent variables have the following appearance:

$$U_{ij} = \beta_j^{'} x_i + \varepsilon_{ij} \qquad (i = 1,...,1040; j = 1,2,3)$$

The deterministic component $\beta_j' x_i$ is composed of the explanatory variables and the inherent parameters. The known vectors of the explanatory variables are $x_i=(x_{i1},...,x_{i,16})$ (i=1,...1040). Thus, in the econometric analysis we include beside the 15 (firm specific) explanatory variables $x_{i1},...,x_{i,15,}$ one (firm specific) constant $x_{i,16}$. The unknown parameter vectors are $\beta_j=(\beta_{j1},...,\beta_{j,16})'$ (j=1,2,3). For the formal identification of the discrete choice models, the parameter vector β_3 is restricted to zero.

The values of the latent variables can not be observed and depend on the stochastic components ε_{ij} which summarize all unobserved factors that influence the employment reaction decision. Observable are the realizations of the following Bernoulli variables (i=1,...,1040; j=1,2,3):

$$D_{ij} = \begin{cases} 1 & \text{if firm } i \text{ chooses category } j \\ 0 & \text{else.} \end{cases}$$

We assume that a firm i chooses category j if U_{ij} is greater than all other $U_{ij'}$ $(j \neq j')$. In this context we can imagine U_{ij} as an attraction measure for the profit with reference to alternative j. The probability that firm i chooses category j is therefore:

$$P_{ij} = P(U_{ij} > U_{ij'}; j \neq j'; j, j' = 1,2,3).$$

The probabilities P_{ij} especially depend on the unknown parameters (summarized in the vector θ) of the respective discrete choice models. With the choice probabilities $P_{ij}(\theta)$ we can specify the loglikelihood function under the assumption that the observations are independent:

$$\ln L = \sum_{i=1}^{1040} \sum_{j=1}^{3} D_{ij} P_{ij}(\theta).$$

4.2. Multinomial Logit and Multinomial Independent Probit approaches

4.2.1. Models

If we therefore assume that the ε_{ij} (i=1,...,1040; j=1,2,3) are independently and identically distributed with Type I extreme value density functions, we obtain the popular Multinomial Logit Model (MLM). In empirical applications the computational attractiveness of this discrete choice model rests upon the closed form expression of the choice probabilities $P_{ij}(\theta)$. In this paper the calculations of the test statistics ("z-statistic") of normality tests (null hypothesis H_0: $\beta_{jk}=0$; j=1,2; k=1,...,16) are based on the quasi-maximum likelihood theory (see White, 1982).

If we assume that the ε_{ij} ($\forall$ i,j) are independently and identically distributed standard normal random variables we come to the Multinomial Independent Probit Model (MIPM). The cardinal difficulty in the application of Multinomial Probit Models is the inconvenient form of the choice probabilities $P_{ij}(\theta)$. Indeed in the MIPM this problem is not of importance. As a result of the independence assumption, the choice probabilities are only characterized by an one-dimensional integral even with a large number of alternatives. That´s why we could apply conventional numerical integration methods for the calculations of the choice probabilities. With regard to the comparison to the estimation in the Flexible Multinomial Probit Model (FMPM) (see section 4.3), we approximate the choice probabilities exclusively with stochastic simulation methods.

With such (unbiased) simulators (see e.g. the overviews in Hajivassiliou et al., 1996, or Vijverberg, 1997) we are able to approximate choice probabilities characterized by multidimensional integrals exactly, too. In this paper we utilize the so-called GHK (Geweke-Hajivassiliou-Keane) simulator (see Börsch-Supan and Hajivassiliou, 1993, Keane, 1994, Geweke et al., 1994). For the GHK approach we have to make repeated sequential (pseudo) random draws from the truncated standard normal distribution. By embedding the simulated choice probabilities in the loglikelihood approach, we apply the simulated loglikelihood method (see e.g. Gourieroux and Monfort, 1996).

For analysing the estimation and testing results systematically, we experiment with the variables that are not pre-determined. Due to the inconsistent findings about the reasonable number R of random draws in the GHK simulator in the literature (see e.g. Börsch-Supan and Hajivassiliou, 1993, Geweke et al., 1997, Ziegler and Eymann, 2001), we consider different numbers of such replications. In addition, we vary the tolerance limit of the gradient of the simulated loglikelihood function. Finally, we examine several starting values at the beginning of the maximization process for the parameters. The calculations of the z-statistics are based on the quasi-maximum likelihood theory again (for the simulated counterparts of classical test statistics see Lee, 1999).

4.2.2. Results

In the MIPM estimation we have experimented with different combinations of starting values, numbers of replications in the GHK simulator and tolerance limits of the gradient of the loglikelihood function. In table 2, we present the estimation and testing results of the MLM and of two exemplary MIPM. In the first MIPM estimation, the number of replications in the GHK simulator is R=50, in the second MIPM estimation it is R=200. The tolerance limit of the gradient of the loglikelihood function varies between 0.001 and 0.0001. Starting values in the first MIPM estimation are 0 and in the second MIPM estimation –2.

We find extremely stable parameter estimates and z-statistics in the Probit Models. This is also the case in all other combinations of starting values, numbers of replications (especially with R=10) and tolerance limits of the gradient of the loglikelihood function. Note that the parameter estimates in the MLM and in the MIPM are not directly comparable because the underlying standard normal and Type I extreme value distribution have different variances. Taking this in consideration, we find extremely strong analogies between the MLM and the MIPM. Merely for the parameters β_{28} and $\beta_{2,15}$ in the MIPM, the hypotheses (H_0: β_{28} =0 resp. H_0: $\beta_{2,15}$ =0) are rejected at a lower level of significance.

Table 2: Maximum likelihood estimates and z-statistics in the MLM and in several MIPM

		MLM		MIPM R=50; tol. lev.:0.001 starting values: 0		MIPM R=500; tol. lev.:0.0001 starting values:-2	
VARIABLE	θ	*estimate*	*z-statistic*	*estimate*	*z-statistic*	*estimate*	*z-statistic*
PRODUCT-INN	β_{11}	*0.810***	*3.23*	*0.574***	*3.04*	*0.560***	*2.96*
	β_{21}	*0.538*	*1.14*	*0.344*	*1.12*	*0.319*	*1.02*
SERVICE-INN	β_{12}	*0.869***	*3.38*	*0.653***	*3.32*	*0.660***	*3.34*
	β_{22}	*0.051*	*0.08*	*0.159*	*0.40*	*0.130*	*0.32*
RECYCLING-INN	β_{13}	*0.050*	*0.19*	*0.009*	*0.05*	*0.007*	*0.04*
	β_{23}	*-2.389***	*-2.15*	*-1.387***	*-2.51*	*-1.344***	*-2.56*
END-OF-PIPE-INN	β_{14}	*0.079*	*0.31*	*0.117*	*0.65*	*0.111*	*0.62*
	β_{24}	*1.303***	*2.80*	*0.823***	*2.96*	*0.817***	*2.95*
MARKET-SHARE	β_{15}	*0.608***	*5.36*	*0.439***	*5.27*	*0.444***	*5.30*
	β_{25}	*0.914***	*4.69*	*0.607***	*4.82*	*0.620***	*4.92*
ENVIRONMEN-TAL-FACTORS	β_{16}	*0.013*	*0.11*	*-0.002*	*-0.03*	*-0.000*	*-0.00*
	β_{26}	*-0.653***	*-3.05*	*-0.425***	*-3.54*	*-0.419***	*-3.52*
COST-REDUCTION	β_{17}	*0.055*	*0.46*	*0.041*	*0.48*	*0.044*	*0.52*
	β_{27}	*0.681***	*2.48*	*0.422***	*2.92*	*0.423***	*2.92*
HARD	β_{18}	*-0.116*	*-0.91*	*-0.087*	*-0.95*	*-0.090*	*-0.99*
	β_{28}	*-0.361*	*-1.55*	*-0.260**	*-1.92*	*-0.262**	*-1.93*
SOFT	β_{19}	*-0.126*	*-1.18*	*-0.065*	*-0.82*	*-0.068*	*-0.85*
	β_{29}	*0.636***	*2.45*	*0.446***	*2.94*	*0.434***	*2.89*
LARGE	$\beta_{1,10}$	*-0.805***	*-2.21*	*-0.502***	*-2.03*	*-0.508***	*-2.04*
	$\beta_{2,10}$	*0.924***	*2.08*	*0.579***	*2.08*	*0.566***	*2.04*
EXPENDITURE-SHARE	$\beta_{1,11}$	*1.051***	*3.61*	*0.669***	*3.75*	*0.668***	*3.72*
	$\beta_{2,11}$	*1.059***	*2.05*	*0.792***	*2.76*	*0.770***	*2.69*
UNIVERSITY	$\beta_{1,12}$	*1.491***	*3.33*	*1.084***	*3.10*	*1.121***	*3.21*
	$\beta_{2,12}$	*-0.869*	*-0.89*	*-0.775*	*-1.14*	*-0.562*	*-0.89*
SALES-EXP	$\beta_{1,13}$	*1.015***	*2.88*	*0.693***	*2.96*	*0.721***	*3.06*
	$\beta_{2,13}$	*-0.185*	*-0.41*	*0.097*	*0.34*	*0.114*	*0.40*
REGULATION	$\beta_{1,14}$	*0.760***	*3.15*	*0.577***	*3.32*	*0.568***	*3.26*
	$\beta_{2,14}$	*0.989***	*2.13*	*0.660***	*2.36*	*0.654***	*2.33*
GERMANY	$\beta_{1,15}$	*0.618***	*2.42*	*0.439***	*2.31*	*0.449***	*2.35*
	$\beta_{2,15}$	*0.954**	*1.90*	*0.748***	*2.47*	*0.764***	*2.53*
CONST	$\beta_{1,16}$	*-4.471***	*-10.40*	*-3.441***	*-11.35*	*-3.464***	*-11.37*
	$\beta_{2,16}$	*-5.620***	*-8.15*	*-4.189***	*-10.01*	*-4.219***	*-9.98*
Loglikelihood at convergence		*-372.901*		*-373.844*		*-373.382*	

Remarks: Significance level 0.1, ** Significance level 0.05.*

Before we interpret our findings we should take into account that the estimation and testing results are based on the restrictive independence assumption in the stochastic components of the discrete choice models. In the MLM this leads to the so-called property of "independence of irrelevant alternatives" (IIA) (see McFadden, 1973). This property implies that the decision between two alternatives is independent of the existence of another category. Due to the independence assumption the MIPM is likewise restrictive and has properties similar to the IIA (see Hausman and Wise, 1978). The analogy of the estimation and testing results in table 2 confirms these considerations.

The problem is that the impacts of the explanatory variables are overestimated in their significance if the distribution assumption in the stochastic components is wrong. This effect corresponds to the omission of relevant explanatory variables in a linear regression model. In order to check the robustness of the previous results with respect to this restrictive property, we introduce correlations in the stochastic model components which is only possible in a Multinomial Probit approach. So we come to the FMPM.

4.3. Flexible Multinomial Probit approach

4.3.1. Model

In the FMPM with three alternatives we have:

$\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{12}, \varepsilon_{i3})' \sim NV(0;\Sigma)$.

Thus the variance covariance matrix Σ contains six different variance and covariance coefficients. Not all variance covariance parameters are formally identifiable (see e.g. Bunch, 1991, Dansie, 1985). In general we can at most identify two variance covariance parameters.

Thus in Σ we restrict the covariances σ_{13} and σ_{23} to zero and the variance σ_3^2 to one. Because of the scaling we restrict in addition the variance σ_2^2 to one. Consequently only one variance and one covariance parameter is freely estimable. In the following we estimate the transformed coefficients σ_1 [$=(\sigma_1^2)^{1/2}$] and ρ_{12} $(=\sigma_{12}/\sigma_1\sigma_2)$ (for details see Ziegler and Eymann, 2001).

In contrast to the MIPM, in the FMPM the dimension of the integrals of the choice probabilities depends on the number of alternatives. Due to this fact in a FMPM with many alternatives estimation is computationally intractable without the introduction of simulation methods. In the present case of three categories a maximum likelihood estimation with numerical integration methods would be possible.

Indeed conventional maximum likelihood estimation is not generally better than the simulated maximum likelihood approach. For example by using the Gauss-Hermite integration the reasonable number of Hermite points is unclear. Furthermore, in view of future examinations of the FMPM with more than three alternatives, where only the simulated maximum likelihood method is computationally tractable, we want to explore the influence of the simulator on the stability of the estimation results.

4.3.2. Results

The results of the FMPM estimations are disappointing at first glance. Variations of the starting values, numbers of replications and tolerance limits of the gradient lead to quite different estimates of the variance covariance parameters. In addition, in several realizations the loglikelihood function obviously converges to local maxima with the consequence that the estimated parameters are implausible in these cases. Partly these results are accompanied by low loglikelihood values in the maximum. Note that the variation of the number *R* in the GHK simulator is not substantial. Thus the inclusion of the GHK simulator is not the decisive factor for the instability of the FMPM estimation in comparison with variations of the tolerance limit of the gradient of the loglikelihood function and of the starting values.

The instability in the parameter estimation seems to be a consequence of the structure of the explanatory variables, instead. We do not have explanatory variables that vary between the alternatives of the dependent variable. Without so-called category specific variables, practical identification of simulated or unsimulated maximum likelihood estimations of FMPM often is difficult. Although the model is formally identified it can exhibit very small variation in the loglikelihood function from its maximum over a wide range of parameter values (see Keane, 1992). This practical estimation problem remains largely unnoticed in the literature and, therefore, further research seems warranted on this.

Furthermore, we find that the assumption of the MIPM (H_0: $\sigma_1=1$, $\rho_{12}=0$) can never be rejected at a significance level of 5%. This composed hypothesis is tested by the simulated equivalent of the likelihood ratio test (see Lee, 1999). The result is remarkable, because the variance parameter σ_1 frequently is significantly different from one (see e.g. the first and the third estimation in table 3).

Nevertheless we often find stable estimation results of the parameters of the explanatory variables although the variance covariance parameters vary widely. Three typical examples are depicted in table 3. The number of random draws *R* varies hereby between 10, 50 and

500, the tolerance limit for the gradient varies between 0.001 and 0.0001 and the three starting values displayed in table 3 are those for the coefficients of the explanatory variables, for σ_1, and for ρ_{12}.

We find that the signs of the parameters of the explanatory variables which are significantly different from zero never change comparing MLM, MIPM and FMPM. Therefore, the estimation results are robust with respect to the discrete choice model specification and the underlying assumptions about the distribution and the dependence respectively independence of the error terms. The significance levels sometimes change, however. All parameters that are significantly different from zero at a level of 5% in the FMPM are significantly different from zero at the same level in the MLM and the MIPM, too (exception: $\beta_{2,15}$ in the MLM). Some variables that have significant impacts in the MLM and MIPM do not have a significant impact in the FMPM, however. An example is the explanatory variable LARGE. Thus according to the FMPM the firm size has in contrast to our hypothesis and the MLM and MIPM estimations no impact on an employment change on a sensible significance level.

Interesting with respect to policy measures is the impact of the different eco-innovation types on employment. Ecological product and service innovations have a clearly (significance level 5%) positive impact on employment increases. Recycling innovations reduce the probability that a firm decreases its employment. These findings are in line with our hypotheses. Firms with end-of-pipe innovations are more inclined to reduce employment which is not in accordance to our prior hypothesis. One possibility to reconcile this finding with our intuition is that end-of-pipe innovations are quite mature in the meanwhile. They were introduced on a major scale in the 1980s. Probably innovations in this field are labour saving investments now and increase the productivity of the environmentally beneficial technology. This is not the case for environmental product and service innovations that are a relatively recent phenomenon. Notice that in the FMPM the impacts of the end-of-pipe and recycling innovations partly have a substantially higher significance level than the impacts of the product and service innovations.

Table 3: Simulated maximum likelihood estimates and simulated z-statistics in several FMPM

		FMPM R=10; tol. lev.:0.0001 starting values: 0.5/2/-0.5		FMPM R=50; tol. lev.:0.001 starting values: 0/0.5/0.5		FMPM R=500; tol. lev.:0.0001 starting values:-0.5/1/0	
VARIABLE	θ	*Estimate*	*z-statistic*	*estimate*	*z-statistic*	*estimate*	*z-statistic*
PRODUCT-INN	β_{11}	0.392^{**}	2.96	0.425^{**}	2.48	0.396^{**}	2.98
	β_{21}	0.333	1.13	0.371	1.27	0.359	1.22
SERVICE-INN	β_{12}	0.453^{**}	3.18	0.490^{**}	2.43	0.453^{**}	3.23
	β_{22}	0.141	0.38	0.170	0.46	0.127	0.35
RECYCLING-INN	β_{13}	-0.030	-0.22	-0.030	-0.17	-0.032	-0.22
	β_{23}	-1.202^{**}	-2.30	-1.059	-1.57	-1.155^{**}	-2.01
END-OF-PIPE-INN	β_{14}	0.092	0.72	0.120	0.81	0.105	0.78
	β_{24}	0.712^{**}	2.48	0.714^{*}	1.95	0.732^{**}	2.25
MARKET-SHARE	β_{15}	0.329^{**}	5.64	0.358^{**}	4.31	0.329^{**}	5.15
	β_{25}	0.591^{**}	4.88	0.587^{**}	4.65	0.588^{**}	4.79
ENVIRONMEN-TAL-FACTORS	β_{16}	-0.017	-0.28	-0.021	-0.28	-0.019	-0.31
	β_{26}	-0.379^{**}	-2.94	-0.361^{*}	-1.90	-0.367^{**}	-2.46
COST-REDUCTION	β_{17}	0.044	0.73	0.047	0.66	0.044	0.72
	β_{27}	0.385^{**}	2.66	0.380^{**}	2.10	0.387^{**}	2.48
HARD	β_{18}	-0.075	-1.17	-0.082	-1.15	-0.076	-1.14
	β_{28}	-0.232^{*}	-1.79	-0.231	-1.59	-0.227^{*}	-1.71
SOFT	β_{19}	-0.037	-0.65	-0.040	-0.60	-0.036	-0.64
	β_{29}	0.409^{**}	2.64	0.360^{*}	1.83	0.391^{**}	2.38
LARGE	$\beta_{1,10}$	-0.320^{*}	-1.80	-0.331	-1.32	-0.317^{*}	-1.77
	$\beta_{2,10}$	0.480	1.63	0.453	1.11	0.484	1.44
EXPENDITURE-SHARE	$\beta_{1,11}$	0.474^{**}	3.77	0.533^{**}	3.16	0.486^{**}	3.90
	$\beta_{2,11}$	0.757^{**}	2.85	0.779^{**}	2.98	0.764^{**}	2.88
UNIVERSITY	$\beta_{1,12}$	0.761^{**}	3.07	0.828^{**}	2.28	0.764^{**}	3.11
	$\beta_{2,12}$	-0.529	-0.87	-0.448	-0.55	-0.453	-0.70
SALES-EXP	$\beta_{1,13}$	0.495^{**}	3.01	0.527^{**}	2.15	0.487^{**}	2.94
	$\beta_{2,13}$	0.125	0.45	0.194	0.53	0.165	0.51
REGULATION	$\beta_{1,14}$	0.409^{**}	3.37	0.450^{**}	3.20	0.417^{**}	3.40
	$\beta_{2,14}$	0.656^{**}	2.48	0.647^{**}	2.56	0.648^{**}	2.52
GERMANY	$\beta_{1,15}$	0.327^{**}	2.44	0.360^{**}	2.29	0.328^{**}	2.44
	$\beta_{2,15}$	0.760^{**}	2.64	0.731^{**}	2.68	0.749^{**}	2.71
CONST	$\beta_{1,16}$	-2.411^{**}	-10.59	-2.617^{**}	-4.01	-2.418^{**}	-11.56
	$\beta_{2,16}$	-4.068^{**}	-9.72	-4.064^{**}	-8.33	-4.083^{**}	-9.41
VARIANCE-COVARIANCE-PARAMETERS	σ_1	0.052^{**}	-2.22	0.415	-1.14	0.071^{**}	-2.57
	ρ_{12}	-0.401	-0.30	0.360	0.25	0.490	0.16
Loglikelihood at convergence		-373.296		-373.233		-372.686	

Remarks: Significance level 0.1, ** Significance level 0.05.*

Larger innovations increase the probability of an employment change according to our hypothesis. This is also the case for the "market share" innovation goal. Obviously, this innovation goal also may lead to the dismissal of employees (probably in firms that responded to an innovation of a competitor). Also innovations induced by regulations increase the propensity to change employment in both directions. As indicated in section 2, the direction of the impact depends on the concrete measures which are implemented by the regulation. In Germany, the propensity to change employment in the wake of environmental innovations is higher than in the other countries.

A high share of highly qualified employees increases the probability of an employment increase. This indicates that also environmental innovations are skill-biased. In other words, enterprises with better skilled workforces are in a better position to increase employment in the wake of an innovation. Not surprisingly, the firms that expect increasing revenues are also more inclined to increase employment after the innovation. On the other hand, cost reductions as an innovation goal as well as a high importance of the soft competition goals (statistically weaker secured) increase the probability of reducing employment after an environmental innovation. It is remarkable, though, that hard competition factors do not have a significant impact on employment changes.

5. Conclusions

Our discrete choice analysis shows that enterprises are influenced by different factors when they decide to increase employment, decrease it or keep employment unchanged in the wake of environmental innovations. Process and product innovations increase the probability that the firm increases employment, while end-of-pipe innovations increase (at a higher significance level) the probability that a firm reduces its employment. We can therefore conclude that environmental process and product innovations have a positive impact on the labour market as well as on environmental goals while end-of-pipe innovations are less beneficial for employment.

Environmental innovations are skill-biased, they have an impact on employment changes in the firm if they are substantial and if they are induced by regulations. Firms expecting an increase in sales expenditures are more prone to increase employment, while firms that want to slash costs by the innovation and compete by soft factors decrease employment more frequently.

These results are robust to the specification of the discrete choice model. Neither the change in the assumptions on the distribution of the error terms between the MLM and the MIPM model nor the relaxation of the independence assumption in the stochastic components in the FMPM lead to substantive differences in the estimation results. Our analysis encounters some problems by the estimation in a FMPM. These problems mainly result from the fact that we only have firm specific explanatory variables which seems a typical situation for this kind of analysis. As an increase in applications for the FMPM can be expected, a systematic analysis of these estimation problems seems necessary. Using Monte-Carlo methods, it could be analysed for example, if the FMPM is still superior to the simple MIPM if no category specific explanatory variables are available.

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