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On the dynamics of product and process innovations: A bivariate random effects probit model

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**Wirtschaftswissenschaftliche Fakultät
der Eberhard-Karls-Universität Tübingen**

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and Process Innovations.
A Bivariate Random Effects
Probit Model**

Gebhard Flaig and Manfred Stadler



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On the Dynamics of Product and Process Innovations

A Bivariate Random Effects Probit Model

Gebhard Flaig and Manfred Stadler

Abstract

Based on a stochastic dynamic model of a firm's optimal innovative behavior we derive a simultaneous equation system for product and process innovations with intertemporal spillover effects. We estimate various versions of the model with dichotomous innovation data at the firm level by using a bivariate dynamic random effects probit model. The data set, provided by the Ifo-Institute, covers the period between 1981 and 1989 and includes 586 firms of the West German manufacturing sector. It turns out that a firm's probabilities of product and process innovations depend positively on dynamic spillover effects even if one controls for firm size, market concentration, demand expectations, labor cost, unobserved heterogeneity and potential endogeneity of the explanatory variables.

1. Introduction

Since Schumpeter's seminal conjectures about the interactions between market structure and innovation, much effort has been devoted to identify the determinants and consequences of innovative activity. In modern empirical analysis, the simple specifications in the context of the traditional Schumpeterian hypotheses (summarized by Kamien, Schwartz 1982, ch. 3) were stepwise enriched by including industry and firm characteristics such as demand expectations, technological opportunities, appropriability conditions, and by accounting for endogeneity of market structure (for excellent surveys see, e.g., Baldwin, Scott 1987, and Cohen, Levin 1989). Unfortunately, most of the firm-specific characteristics are not directly observable. Nevertheless, by applying an appropriate fixed or random effects estimator, one can econometrically capture such unobserved heterogeneity of firms in a meaningful way (see Geroski 1990, Laisney, Lechner, Pohlmeier 1992, König et al. 1992).

One still neglected issue in the econometric literature is the role of dynamic spillovers in the firms' innovation process. As pointed out by Cohen, Levinthal (1989), innovative activity not only creates new products and processes, but in turn enhances the firms' ability to identify, assimilate, and exploit further technological knowledge from the environment. Indeed, intra- and inter-industry spillovers of know-how play an important role in determining innovative activity (see Jaffe 1986, Bernstein, Nadiri 1989). However, these positive externalities generated by intra- and inter-industry spillovers between firms are only part of the story. There may well be internal spillover effects which work over time within a firm. An innovation success at present may raise the successful firm's innovative activity in the future. The related "success breeds success" hypothesis is usually interpreted in an indirect way by assuming that innovations change the market structure in favor of the successful firms by allowing them to build up market power (see Mansfield 1968, Phillips 1971, Stoneman 1983). In Flaig, Stadler (1994) we suggested a more direct interpretation of dynamic intra-firm spillovers. Technological success may raise future profit opportunities of innovations, thereby inducing more innovative activity in the future. By applying a bivariate dynamic random effects model for the realization of product and process innovations, convincing empirical evidence was found for these dynamic intra-firm spillovers. Since the data cover only a rather short time period and include many missing observations, we were forced to control only for one innovation lag. In the present paper, an extended data set with much more observations is used to prove the robustness of our empirical results and to provide some additional and novel evidence. We therefore generalize our theoretical and empirical model by allowing for more lags. In addition, we extend the model by accounting for contemporary correlation between product and process innovations as well as for time-specific effects.

The paper is organized as follows. In Section 2 we present a rather general stochastic innovation model, explaining the firms' optimal activities in product and process innovations in terms of past innovative activity and expectations about the future environment. In Section 3 the econometric framework of our bivariate dynamic random effects probit model is developed. A description of the data is given in Section 4. Section 5 presents the empirical results where the set of explanatory variables is stepwise enriched. Section 6 finally summarizes the findings in some concluding remarks.

2. A Theoretical Model of the Innovation Process at the Firm Level

According to the decision-theoretic approach of innovative behavior we assume that firms maximize their expected present value of profits, J , over an infinite time horizon by simultaneously choosing optimal sequences of both product and process innovative activity, $Y_t = (Y_{t,1}, Y_{t,2})'$. The innovation profit is the discounted stream of rents flowing from innovative activity Y_t in period t , net of innovation cost. To explicitly solve the model and to obtain tractable estimation equations, we use the quadratic specification $A_t'Y_t - (1/2) Y_t'BY_t$ for the profit function, where $A_t=(a_{t,1}, a_{t,2})'$ is a time-varying (2×1) coefficient vector and B is a constant positive definite (2×2) coefficient matrix. In addition, we account for dynamic interrelations by allowing for a firm's innovations realized in previous periods to change the marginal profit of the current period's innovations. We add a quadratic spillover term, $(1/2) [D(L)Y_t]' [D(L)Y_t]$, to the profit function where $D(L)$ is defined as the matrix polynomial $D(L) = D_0 + D_1L + D_2L^2$ with $D_m, m=0,1,2$ as (2×2) coefficient matrices and L as lag operator. Of course, this quadratic specification, which yields linear decision rules, is somewhat restrictive. However, more general specifications lead to intractable problems for the estimation of the model. It is assumed that the current innovation profit is strictly concave in Y_t . Discounting future profits with the factor δ , each firm maximizes its expected discounted value function

$$(1) \quad J_0 = E_0 \sum_{t=0}^{\infty} \delta^t \left\{ A_t'Y_t - (1/2) Y_t'BY_t + (1/2) [D(L)Y_t]' [D(L)Y_t] \right\}$$

where E_t is the expectation operator in period t . The time-path of Y_t is to be chosen for all $t \geq 0$, given the initial values for $t < 0$. Differentiating (1) with respect to Y_t and rearranging yields the Euler equation

$$(2) \quad \left\{ B - D(\delta L^{-1})' D(L) \right\} E_t Y_t = E_t A_t ,$$

which is a second-order linear difference equation for the optimal values of Y as expected in period t . It allows for replanning in each future period if new information becomes available.

By making use of an appropriate factorization (see, e.g. Hansen, Sargent 1981 and Sargent 1987, ch. IX), the solution equation system can be written as

$$(3) \quad (C_0 + C_1L + C_2L^2) \begin{pmatrix} Y_{t,1} \\ Y_{t,2} \end{pmatrix} = \sum_{h=1}^4 M_h \sum_{s=0}^{\infty} (\lambda_h \delta)^s E_t \begin{pmatrix} a_{t+s,1} \\ a_{t+s,2} \end{pmatrix},$$

where λ_h , $h=1,2,3,4$ are four factorization parameters and C_m , $m=0,1,2$ and M_h , $h=1,2,3,4$ are (2×2) matrices, depending on the coefficients of the B and D matrices. In our empirical analysis we treat $a_{t,j}$ as shift parameters for the marginal values of product and process innovations. These shift parameters are assumed to depend on some observable variables, unobservable firm characteristics, and unobservable time-specific effects. The observable variables are summarized in the vector $x = (S, H, Q, W)'$ and include firm size, S, market concentration, H, expected demand, Q, and labor cost share, W. The unobservable firm-specific characteristics are represented by a latent variable, ϵ , which is assumed to be constant over time and known to the firms. Using this latent variable we account for some individual firms' attributes like creativity, intuition, appropriability of innovation rents and capability to reap technological opportunities. The time-specific effect, η_t , which is assumed to be identical for all firms captures economywide impacts on the firms' innovative activity. Using this time effect, we admit that supply and demand shocks, changes in science based technological knowledge, and innovation policy can influence innovative activity of firms. To this end, we endogenize the shift parameters for both product and process innovations by using the linear specification

$$(4) \quad a_{t,j} = \tilde{\alpha}_j' x_t + \tilde{\gamma}_j \epsilon + \tilde{\mu}_j \eta_t, \quad j=1,2.$$

We add a stochastic error term $\tilde{u}_t = (\tilde{u}_{t,1}, \tilde{u}_{t,2})'$ on the right hand side of (3) that reflects the intrinsically uncertain nature of the innovation process. As is well known, innovative outcome is hard to control when serendipity plays an important role (see, e.g., Kamien, Schwartz 1982, p. 58). Some firms are just lucky in performing an innovation but not all planned innovation projects end up with the intended success. Assuming that firms have static expectations about the observable variables x , using the specification (4) for the shift parameters, and appending the error term, we derive from (3) the following solution function for product and process innovations:

$$(5) \quad \begin{pmatrix} Y_{t,1} \\ Y_{t,2} \end{pmatrix} = C_0^{-1} \left\{ -C_1 \begin{pmatrix} Y_{t-1,1} \\ Y_{t-1,2} \end{pmatrix} - C_2 \begin{pmatrix} Y_{t-2,1} \\ Y_{t-2,2} \end{pmatrix} + \begin{pmatrix} \tilde{\alpha}_1' x_t \\ \tilde{\alpha}_2' x_t \end{pmatrix} + \begin{pmatrix} \tilde{\gamma}_1 \epsilon \\ \tilde{\gamma}_2 \epsilon \end{pmatrix} + \begin{pmatrix} \tilde{\mu}_1 \eta_t \\ \tilde{\mu}_2 \eta_t \end{pmatrix} + \begin{pmatrix} \tilde{u}_{t,1} \\ \tilde{u}_{t,2} \end{pmatrix} \right\}.$$

In principle, the restrictive assumption of static expectations could be relaxed by modeling the future expected values of x as a function of observed past values. However, this would not only reduce the number of observations in our panel data set but would also dramatically increase the number of parameters to be estimated.

The coefficients $\tilde{\alpha}_j^1$, $\tilde{\gamma}_j$, and $\tilde{\mu}_j$ depend in a complicated way on the coefficients $\tilde{\tilde{\alpha}}_j^1$, $\tilde{\tilde{\gamma}}_j$, $\tilde{\tilde{\mu}}_j$, the discount factor δ , the factorization parameters λ_h , and the components of the matrices M_h . In a more tractable formulation, (5) can be written as

$$(6) \quad Y_{t,j} = \sum_{k=1}^2 \sum_{s=1}^2 \psi_{j,k,s} Y_{t-s,k} + \alpha_j^1 x_t + \gamma_j \epsilon + \mu_j \eta_t + u_{t,j}, \quad j=1,2,$$

where the coefficients depend on the coefficients of the matrices C_0 , C_1 , C_2 , and on the coefficients $\tilde{\alpha}_j^1$, $\tilde{\gamma}_j$, and $\tilde{\mu}_j$. The error term is defined as $u_j \equiv c_j (\tilde{u}_1, \tilde{u}_2)'$ with c_j as row j of the matrix C_0^{-1} . Thus, the error terms u_j are not independent of each other. In our econometric model, we allow for a non-zero contemporary correlation σ_{12} between the residuals of both types of innovation. The solution equation (6) expresses innovative activity in terms of once and twice lagged product and process innovations and in terms of the observable and unobservable explanatory variables. The occurrence of path dependence is caused by the impact of cumulativeness of innovative capabilities at the firm level which plays a crucial role in our model of the intra-firm innovation process (see Dosi 1988, p. 1161 for an informal treatment). The equation system (6) will serve as baseline model for the empirical analysis.

3. Econometric Specification of the Bivariate Dynamic Random Effects Probit Model

In our panel data set innovative activities are only observed as dichotomous variables, $Y_{i,t,j}^D$, indicating whether or not a firm i ($i=1,\dots,N$) has successfully implemented at least one product ($j=1$) or process ($j=2$) innovation in period t ($t=1,\dots,T$). Therefore, we treat product and process innovative activities $Y_{i,t,j}$ as continuous latent variables and assume that innovations are realized, if and only if these variables exceed innovation type specific thresholds $\tilde{Y}_j > 0$:

$$(7) \quad Y_{i,t,j}^D = \begin{cases} 1, & \text{iff } Y_{i,t,j} \geq \tilde{Y}_j \\ 0, & \text{iff } Y_{i,t,j} < \tilde{Y}_j \end{cases}, \quad i=1,\dots,N, \quad t=1,\dots,T, \quad j=1,2.$$

These thresholds can be rationalized by the existence of fixed cost that appear when an innovation is undertaken. In our theoretical model, innovative activities $Y_{i,t,j}$ depend on innovation efforts of the two previous periods. Unfortunately, these variables are not observable. This fact leads to serious econometric problems which are not yet solved in the literature (for a first, but in many respects unsatisfactory attempt to estimate a habit persistence model see Grether, Maddala 1982). One possible way to proceed is to substitute the latent endogenous variables, Y , on the right hand side of (6) by their realization values, Y^D . This

reformulation enables us to build upon the bivariate dynamic random effects probit model developed in Flaig, Stadler (1994) which is itself an extension of the univariate model suggested by Heckman (1981a).

A further econometric problem is the specification of the time effects η_t in our non-linear model. In order to keep things tractable, we specify η_t as a fixed effect. This procedure allows us to treat the time effects as dummy variables D in the extended vector $x = (S, H, Q, W, D)'$ of the observed variables. Incorporating these refinements in (6) we can write the structural equations for the latent variables Y as

$$(8) \quad Y_{i,t,j} = z_{i,t,j}(\varepsilon_i) + u_{i,t,j},$$

whereby

$$(9) \quad z_{i,t,j}(\varepsilon_i) \equiv \sum_{k=1}^2 \sum_{s=1}^2 \psi_{j,k,s} Y_{i,t-s,k}^D + \alpha_j x_{i,t} + \gamma_j \varepsilon_i, \quad j=1,2.$$

We assume that ε_i and $u_{i,t,j}$ follow a multivariate standard-normal distribution with

$$(10) \quad E(\varepsilon_i) = E(u_{i,t,j}) = 0 \quad \text{for all } i, t, j,$$

$$E(\varepsilon_i \varepsilon_{i'}) = \begin{cases} 1, & \text{for } i = i' \\ 0, & \text{otherwise} \end{cases},$$

$$E(u_{i,t,j} u_{i',t',j'}) = \begin{cases} 1, & \text{for } i = i', t = t', j = j', \\ \sigma_{12} & \text{for } i = i', t = t', j \neq j', \\ 0, & \text{otherwise} \end{cases}$$

$$E(\varepsilon_i u_{i',t',j'}) = 0 \quad \text{for all } i, i', t, j,$$

$$E(u_{i,t,j} x_{i',t',j'}) = 0 \quad \text{for all } i, i', t, t', j, j',$$

$$E(\varepsilon_i x_{i',t',j'}) = 0 \quad \text{for all } i, i', t, j.$$

Since we only observe qualitative data, we arbitrarily normalize the variances of ε and u to one, even if it would be possible to allow for time-varying variances. In extension of the econometric model in Flaig, Stadler (1994) we allow for a contemporary correlation σ_{12} in the realization errors $u_{i,t,j}$ for a firm's product and process innovations in a given period. However, the error terms are assumed to be uncorrelated over time and over firms. The assumption that

the unobservable effect ε_i is independent of all the x -variables is undoubtedly restrictive. However, we will later allow for a correlation between x and ε , where we have to assume that the true relationship is linear and the residual ξ_i of a linear projection of ε_i on x_i is normally distributed (see Chamberlain 1984). The projection of ε_i on x_i measures the expectation of ε_i conditional on x_i and captures the correlations between the observed and unobserved factors which determine the innovation decisions.

To derive the likelihood function, we define the joint probability distributions of $Y_{i,t,j}^D$, $j=1,2$, given the lagged values for $Y_{i,t-s,j}^D$, the observed values for $x_{i,t}$, and the firm-specific effect ε_i :

$$\begin{aligned}
 (11) \quad \Pr(Y_{i,t,1}^D = 1, Y_{i,t,2}^D = 1) &= \Pr(u_{i,t,1} \leq z_{i,t,1}(\varepsilon_i), u_{i,t,2} \leq z_{i,t,2}(\varepsilon_i)) \\
 &\equiv \Phi(z_{i,t,1}(\varepsilon_i), z_{i,t,2}(\varepsilon_i), \sigma_{12}), \\
 \Pr(Y_{i,t,1}^D = 1, Y_{i,t,2}^D = 0) &= \Pr(u_{i,t,1} \leq z_{i,t,1}(\varepsilon_i), u_{i,t,2} > z_{i,t,2}(\varepsilon_i)) \\
 &\equiv \Phi(z_{i,t,1}(\varepsilon_i), -z_{i,t,2}(\varepsilon_i), -\sigma_{12}), \\
 \Pr(Y_{i,t,1}^D = 0, Y_{i,t,2}^D = 1) &= \Pr(u_{i,t,1} > z_{i,t,1}(\varepsilon_i), u_{i,t,2} \leq z_{i,t,2}(\varepsilon_i)) \\
 &\equiv \Phi(-z_{i,t,1}(\varepsilon_i), z_{i,t,2}(\varepsilon_i), -\sigma_{12}), \\
 \Pr(Y_{i,t,1}^D = 0, Y_{i,t,2}^D = 0) &= \Pr(u_{i,t,1} > z_{i,t,1}(\varepsilon_i), u_{i,t,2} > z_{i,t,2}(\varepsilon_i)) \\
 &\equiv \Phi(-z_{i,t,1}(\varepsilon_i), -z_{i,t,2}(\varepsilon_i), \sigma_{12}),
 \end{aligned}$$

where $\Phi(\kappa_1, \kappa_2, \sigma_{12})$ represents the value of the standardized bivariate normal distribution function with the correlation coefficient σ_{12} at the points κ_1 and κ_2 . The threshold variables \tilde{Y}_j are absorbed in the constant term included in x and are therefore part of $z_{i,t,j}$. For a given value of ε_i and the initial values, the conditional probability of an observed sequence $(Y_{i,t,1}^D, Y_{i,t,2}^D)$, $t=1, \dots, T$, can be expressed by

$$\begin{aligned}
 (12) \quad \Pr(Y_{i,1,1}^D, Y_{i,1,2}^D, Y_{i,2,1}^D, Y_{i,2,2}^D, \dots, Y_{i,T,1}^D, Y_{i,T,2}^D) = \\
 \prod_{t=1}^T \Phi(z_{i,t,1}(\varepsilon_i) (2Y_{i,t-1,1}^D - 1), z_{i,t,2}(\varepsilon_i) (2Y_{i,t-1,2}^D - 1), \sigma_{12}(2Y_{i,t-1,1}^D - 1)(2Y_{i,t-1,2}^D - 1)).
 \end{aligned}$$

A serious problem is the estimation of the initial values $Y_{i,-1,j}^D$ and $Y_{i,0,j}^D$. Since the error terms $v_{i,t,j} \equiv \gamma_j \varepsilon_i + u_{i,t,j}$ are serially correlated, they cannot be taken as exogenous. Therefore,

we follow the procedure suggested by Heckman (1981b) and approximate the unobserved initial values by a linear function of the observed exogenous variables in the periods -1 and 0 and the firm-specific effect:

$$(13) \quad Y_{i,t,j} = \alpha_{0,j} x_{i,t} + \gamma_{0,j} \varepsilon_i + u_{i,t,j}, \quad t = -1, 0.$$

Then the conditional probabilities for all $Y_{i,t,j}$, $t = -1, 0, 1, \dots$, given ε_i , can be expressed as

$$(14) \quad \Pr(Y_{i,-1,1}^D, Y_{i,-1,2}^D, Y_{i,0,1}^D, Y_{i,0,2}^D, \dots, Y_{i,T,1}^D, Y_{i,T,2}^D) = \prod_{t=-1}^T \Phi(z_{i,t,1}(\varepsilon_i) (2Y_{i,t,1}^D-1), z_{i,t,2}(\varepsilon_i) (2Y_{i,t,2}^D-1), \sigma_{12}(2Y_{i,t,1}^D-1)(2Y_{i,t,2}^D-1)),$$

where the z-values for the periods -1 and 0 are defined as $z_{i,t,j}(\varepsilon_i) \equiv \alpha_{0,j} x_{i,t} + \gamma_{0,j} \varepsilon_i$, $t = -1, 0$, $j=1, 2$. The unconditional joint probability L_i for all observations $(Y_{i,-1,1}^D, Y_{i,-1,2}^D, Y_{i,0,1}^D, Y_{i,0,2}^D, \dots, Y_{i,T,1}^D, Y_{i,T,2}^D)$ is obtained by multiplying (14) with $\varphi(\varepsilon_i)$ and integrating over ε_i :

$$(15) \quad L_i = \int_{-\infty}^{\infty} \prod_{t=-1}^T \Phi(z_{i,t,1}(\varepsilon_i)(2Y_{i,t,1}^D-1), z_{i,t,2}(\varepsilon_i)(2Y_{i,t,2}^D-1), \sigma_{12}(2Y_{i,t,1}^D-1)(2Y_{i,t,2}^D-1)) \varphi(\varepsilon_i) d\varepsilon_i$$

where $\varphi(\varepsilon_i)$ denotes the standard normal density function. L_i represents the contribution of firm i to the likelihood function. The log-likelihood function for all observations $i=1, \dots, N$ is given by

$$(16) \quad \ln L = \sum_{i=1}^N \ln L_i.$$

The computation of the likelihood function requires a numerical integration in (15) which is performed by using the Gauss-Hermite-procedure (see Butler, Moffitt 1982). If the model is correctly specified, the ML-estimator is consistent, asymptotically efficient, and asymptotically normal. The asymptotic variance-covariance matrix is estimated by the OPG (outer product of gradient)-method (see Berndt et al. 1974):

$$(17) \quad \hat{V}_{\hat{\theta}} = \left\{ \sum_{i=1}^N [(\partial \ln L_i / \partial \theta) (\partial \ln L_i / \partial \theta)'] \Big|_{\theta = \hat{\theta}} \right\}^{-1}$$

where all parameters are collected in the vector θ . The derivatives are numerically calculated at the estimated parameter values $\hat{\theta}$. All calculations and estimates were performed with GAUSSI, version 3.1.

An alternative estimator for the variance-covariance matrix could in principle be constructed by the expression $A^{-1}VA^{-1}$ with A as the matrix of second derivatives (see Amemiya 1985, ch. 4) which would be consistent under some misspecification of the model. We have refrained from this procedure as we would have to calculate the derivatives numerically and there is some indication in the literature that especially numerically computed second derivatives are prone to severe approximation errors.

4. The Panel Data Set

We estimate our model with a balanced panel for 586 firms in 21 industries of the West German manufacturing sector. For technical reasons, our program can handle only balanced panels. But we should mention here that sample mortality ignored in our model may induce severe sample selection problems. However, an analysis of the attrition problem would go far beyond the scope of our paper. The data were collected by the Ifo-Institute and are part of the Ifo-Konjunkturtest (see Oppenländer, Poser 1989, p. 269). The data set includes realized product and process innovations as dichotomous variables, the number of employees, demand expectations, and the industrial classification of each firm. The period ranges from 1981 to 1989. The industrial classification of the firms enabled us to merge structural variables at the two-digit industry level. Data for nominal value added and gross labor income are taken from the yearly disaggregated national income accounts of the Statistisches Bundesamt, Fachserie 18. The Herfindahl indices of market concentration are taken from the Statistisches Bundesamt, Fachserie 4, Reihe S. 9.

Our complete data set consists of the following variables:

- Y_1^D : Product innovations realized (0: no; 1: yes)
- Y_2^D : Process innovations realized (0: no; 1: yes)
- S: Firm size, measured by the number of employees
- H: Market concentration, measured by the Herfindahl index
- Q: Expected change of demand for the product (-2: strongly decreasing, -1: weakly decreasing; 0: no change; 1: weakly increasing, 2: strongly increasing) .
- W: Share of labor cost, measured by the ratio of gross labor income to nominal value added.

Treating the ordinal variable Q as a qualitative variable may seem to be a problematic procedure. But using a set of dummy variables requires the estimation of additional 12 parameters. The number of firms and the mean values of the variables at the industry level are summarized in Table 1.

Table 1: Number of Firms (N) and Mean Values of the Variables at the Industry Level

No	Industry	N	Y_1^D	Y_2^D	S ($\times 10^3$)	H ($\times 10^{-1}$)	Q	W
25	Stones and clay	9	0.346	0.383	0.079	0.049	-0.049	0.619
31	Structural metal products	8	0.139	0.264	0.261	0.135	-0.155	0.865
32	Mechanical engineering	118	0.721	0.639	0.968	0.044	0.547	0.831
33	Road vehicles	22	0.732	0.742	3.582	1.031	0.526	0.727
36	Electrical engineering	68	0.675	0.642	0.733	0.522	0.374	0.753
37	Precision and optical inst.	23	0.691	0.705	0.647	0.164	0.597	0.719
38	Finished metal goods	43	0.654	0.623	0.218	0.047	0.180	0.728
39	Musical instr., toys etc.	4	0.833	0.500	0.097	0.099	0.347	0.529
40	Chemical products	9	0.852	0.753	0.333	0.372	0.553	0.692
51	Ceramic goods	14	0.818	0.746	0.799	0.693	0.201	0.800
52	Glass	14	0.730	0.802	0.464	0.345	0.450	0.677
53	Wood working	7	0.143	0.175	0.095	0.114	-0.053	0.755
54	Wood products	32	0.628	0.517	0.279	0.024	0.442	0.773
55	Paper manufacturing	18	0.352	0.364	0.217	0.542	0.407	0.661
56	Paper processing	16	0.292	0.312	0.183	0.099	0.223	0.699
57	Printing and duplicating	33	0.327	0.370	0.102	0.051	0.455	0.704
58	Plastic Products	41	0.621	0.607	0.180	0.042	0.617	0.686
61/62	Leather	14	0.657	0.564	0.221	0.143	0.044	0.673
63	Textiles	50	0.596	0.576	0.333	0.033	0.145	0.753
64	Clothing	19	0.561	0.421	0.338	0.040	0.051	0.716
68	Food and beverages	24	0.394	0.412	0.148	0.029	0.205	0.554
Total		586	0.607	0.583	0.594	0.188	0.368	0.739

5. Empirical Results and Illustrations

We estimate the model in various versions. In a first stage, we use a rather conventional bivariate probit model neglecting firm and time specific effects as well as the potential endogeneity of the observed explanatory variables. The observable variables that determine the shift parameters of our theoretical model include firm size, market concentration, expected

demand, and the share of labor cost. In the following, we stepwise extend the model by referring to random firm and fixed time effects, and by accounting for potential endogeneity of the explanatory variables. The estimated coefficients, t-statistics, and log-likelihood values for the various versions are reported in Table 2. The upper part of the table presents the coefficients for the equations we used to approximate the initial conditions. The equations for initializing the stochastic innovation processes should not be interpreted in a structural manner, but the coefficients are significant and have the expected signs. Firm size, market concentration, demand expectations, and the share of labor cost have a positive impact on the realization of product innovations as well as on process innovations. However, crucial for our interpretations are the results for the structural equations presented in the lower part of Table 2. These results are more carefully discussed in the following sections.

A. Market Structure and Dynamic Spillovers in the Innovation Process

The first two columns in Table 2 contain the results for the bivariate probit model with simple data pooling. This kind of econometric model lies in the tradition of the innovation probit models of König, Zimmermann (1986), Zimmermann (1989), Pohlmeier (1992), but is extended by dynamic spillover effects and contemporary correlation between product and process innovations. We find strong evidence that past realized product and process innovations raise the probability of realizing both types of innovation in the current period. As expected, the impacts of lagged realized innovations of the same type dominate the impacts of lagged innovations of the other type, and the impacts of once lagged innovations dominate the impacts of twice lagged innovations. These appealing results, which apply for the coefficient values as well as for the t-statistics, indicate strong structural state dependence in a firm's innovation process. This evidence lends further support to the success breeds success hypothesis as suggested in Flaig, Stadler (1994).

The inclusion of the market structure variables in our data set was motivated by some Schumpeterian hypotheses intensively discussed in the literature (see e.g. the survey by Kamien, Schwartz 1982, ch. 3). Firm size has a positive significant impact on both types of innovations. Several arguments in favour of this size effect are offered in the Schumpeterian literature. Capital market imperfections could confer an advantage on large firms in securing external finance of innovative activity. Due to economies of scope in production, large diversified firms may be able to exploit unforeseen innovation success more efficiently. Finally, there may be some complementary marketing efforts or activities for gaining control over the channels of distribution which are better developed within large firms. Possibly, small and large firms respond differently to various stimuli (see e.g. Acs, Audretsch 1988, 1990), but we do not intend to analyze such size effects in this study.

Contrary to the initial conditions, the market concentration variable, represented by the Herfindahl index, seems to be irrelevant for innovative success if one accounts for innovation dynamics. This result is probably caused by the weakness of the Herfindahl index in characterizing the structure of the relevant market for a special firm. In an extended version, not presented here, we found no additional influence of squared firm size and squared market concentration. Thus, there is no evidence for non-linear relationships between these variables and innovative activity. The highly significant positive coefficients of the expected change in market demand supports the demand pull hypothesis suggested by Schmookler (1966), indicating that the expectation of a growing demand spurs innovative activity. The share of labor cost has a positive but insignificant influence on innovations. However, it will be shown that this cost push variable becomes significant in a more complete specification. The correlation coefficient σ_{12} between the error terms of the equations for product and process innovations is positive and highly significant. Thus, in order to get efficient parameter estimates, the correlation between these error terms should not be neglected in an appropriate econometric model. The success probabilities of both types of innovation tend to respond to an exogenous shock in the same direction.

B. The Role of Unobserved Heterogeneity

In versions 2 and 3 of our model we enrich the set of explanatory variables by random firm-specific effects and fixed time-specific effects. The unobserved heterogeneity which reflects differences in the firms' creativity, intuition, capability to exploit technological opportunities, and appropriability of innovation rents seems to be crucial for explaining innovative success at the firm level (see also Geroski 1990, Laisney, Lechner, Pohlmeier 1992, König et al. 1992). In the initial conditions as well as in the structural equations, the coefficients of the firm-specific effects are highly significant. The other explanatory variables remain significant or become significant as in the case of the cost push variable. High labor cost spur product and process innovations, probably to escape the cost trap. The dynamic spillover effects decline a little but remain highly significant. To test the overall significance of the inclusion of the firm-specific effect, we employed the likelihood ratio (LR) test procedure. The LR test statistic is asymptotically distributed as a χ^2 random variable with degrees of freedom equal to the number of parameter restrictions in the initial conditions and in the structural equations. The critical value of $\chi^2_{0.05}(4)$ at the five percent level of significance is 9.5. Thus, the LR-test statistic of 241.8 against version 1 reflects the importance of unobserved heterogeneity in the innovation process. Accordingly, simple probit models that ignore unobserved firm-specific effects produce inconsistently estimated coefficients (this is in contrast to static models where a simple probit estimator without random effects is consistent (see Robinson 1982)). However, our dynamic random effects probit model seems to be an appropriate method for analyzing both heterogeneity and structural dynamics of firms' innovative activity.

Version 3 includes time dummies as additional explanatory variables in the model. Due to scarce space, the estimated parameters for these dummy variables are not presented here. There appears no clear pattern of the parameter values and their significance. Some coefficients are significant, others are not. There is, for example, no coincidence with the German business cycle or changes in the German innovation policy. Nevertheless, the LR test statistic of 24.8 against version 2 shows, compared to the critical value of $\chi^2_{0.05}(16)=23.7$, that the overall time-specific effect plays a non-negligible role in explaining the innovation process.

C. On the Simultaneity Problem

A potential problem we have not discussed so far is that the observed variables may not be exogenous with respect to the unobserved firm-specific effect. If there are non-zero correlations between ε_i and x_i , the estimated coefficients are inconsistent. Following the lines suggested by Chamberlain (1984, pp. 1270), we specify the random effect ε_i as a linear function of the observed variables x_i and an unobserved error term ξ_i which is assumed to be independent of the explanatory variables and standard-normally distributed. In order to keep the model tractable we restrict the parameters of all leads and lags of each explanation factor to take the same value. The random effect can then be decomposed in

$$(18) \quad \varepsilon_i = \beta' \bar{x}_i + \xi_i,$$

where \bar{x}_i denotes the vector of firm-specific mean values for S, H, Q, and W. Thereby, the econometric model and the likelihood function remain essentially the same. Only the set of explanatory variables has to be augmented by the vector \bar{x}_i and the integral in (15) has to be calculated with respect to ξ_i instead of ε_i . The calculated LR statistic of 59.2 against version 3, compared to the critical value of $\chi^2_{0.05}(16)=26.3$ indicates that the mean values are significant explanatory variables. However, the t-statistics of the single parameters show that only the coefficients of the mean values of expected demand, \bar{Q}_i , are significant. This result holds for the initial conditions as well as for the structural equations. Firm size, market concentration and share of labor cost are surprisingly uncorrelated with the firm-specific effect. Version 4 in Table 2 presents therefore the estimation results with only \bar{Q} as an additional regressor. To avoid confusion we continue to denote the firm-specific effect with ε (instead of ξ). The calculated LR statistic of 51.2 for this reduced model against version 3, compared to the critical value of $\chi^2_{0.05}(4)=9.5$, indicates the importance of the mean values of the firms' demand expectations. As is plausible, the inclusion of \bar{Q} reduces the direct impact of Q on product and process innovations. The influence of the other explanatory variables does not change very much. Especially the effects of dynamic spillovers and of unobserved heterogeneity prove to be extremely robust to all implemented extensions.

Table 2 *

Variable	Version 1		Version 2		Version 3		Version 4	
	Product	Process	Product	Process	Product	Process	Product	Process
	Initial Conditions				Initial Conditions			
CON	-1.59 (-4.11)	-1.35 (-3.29)	-1.96 (-3.25)	-1.52 (-2.82)	-1.99 (-3.27)	-1.50 (-2.75)	-2.07 (-3.37)	-1.54 (-2.85)
S	0.06 (4.97)	0.11 (3.11)	0.08 (4.11)	0.11 (2.45)	0.08 (4.10)	0.12 (2.46)	0.06 (3.05)	0.10 (2.15)
H	0.36 (2.59)	0.44 (3.13)	0.45 (1.92)	0.53 (2.60)	0.45 (1.91)	0.53 (2.58)	0.47 (2.13)	0.53 (2.77)
Q	0.21 (4.99)	0.22 (4.97)	0.18 (3.01)	0.19 (3.55)	0.17 (2.99)	0.18 (3.48)	0.08 (1.10)	0.07 (1.09)
\bar{Q}	-	-	-	-	-	-	0.59 (4.92)	0.57 (5.44)
W	2.15 (4.31)	1.68 (3.16)	2.68 (3.43)	1.90 (2.73)	2.78 (3.55)	1.99 (2.83)	2.63 (3.33)	1.81 (2.60)
ϵ	-	-	0.92 (11.64)	0.69 (10.28)	0.91 (11.52)	0.69 (10.25)	0.86 (11.62)	0.64 (10.01)
	Structural Equations				Structural Equations			
CON	-1.31 (-5.41)	-1.33 (-5.88)	-1.03 (-2.85)	-1.10 (-3.93)	-1.20 (-3.15)	-1.17 (-3.99)	-1.26 (-3.17)	-1.22 (-3.91)
$Y^D_{-1,1}$	0.83 (14.43)	0.37 (6.95)	0.49 (7.08)	0.11 (1.80)	0.49 (6.78)	0.11 (1.68)	0.44 (6.04)	0.07 (1.01)
$Y^D_{-2,1}$	0.56 (10.73)	0.25 (4.57)	0.21 (3.22)	0.01 (0.07)	0.20 (3.00)	-0.00 (-0.01)	0.16 (2.30)	-0.04 (-0.56)
$Y^D_{-1,2}$	0.37 (7.06)	0.71 (13.19)	0.21 (3.41)	0.61 (10.86)	0.20 (3.20)	0.62 (10.73)	0.17 (2.72)	0.60 (10.41)
$Y^D_{-2,2}$	0.18 (3.05)	0.44 (8.04)	0.01 (0.09)	0.34 (5.61)	-0.00 (-0.01)	0.33 (5.35)	-0.03 (-0.48)	0.31 (5.01)
S	0.25 (8.02)	0.24 (6.98)	0.32 (5.81)	0.27 (6.70)	0.31 (5.66)	0.27 (6.59)	0.31 (5.21)	0.26 (6.09)
H	-0.02 (-0.22)	-0.01 (-0.04)	0.07 (0.42)	0.06 (0.45)	0.06 (0.40)	0.05 (0.42)	0.11 (0.68)	0.08 (0.62)
Q	0.26 (8.92)	0.24 (8.26)	0.32 (8.81)	0.27 (8.31)	0.32 (8.66)	0.27 (7.94)	0.24 (5.01)	0.22 (4.85)
\bar{Q}	-	-	-	-	-	-	0.57 (5.74)	0.34 (4.27)
W	0.41 (1.25)	0.50 (1.60)	0.81 (1.66)	0.73 (1.89)	1.03 (2.01)	0.86 (2.13)	1.04 (1.94)	0.89 (2.10)
ϵ	-	-	0.75 (10.62)	0.47 (8.03)	0.77 (10.72)	0.48 (8.06)	0.82 (12.11)	0.52 (9.11)
σ_{12}		0.60 (40.23)		0.50 (25.70)		0.50 (25.52)		0.50 (24.83)
ln L	-5228.27		-5107.37		-5094.99		-5069.40	

* t-values in parentheses

Our procedure in this section deals with the possible correlation between ϵ and x . One may, however, think of more general simultaneity problems arising when the residual u and innovative activity Y have an influence on firm size, demand or labor cost. The analysis of this problem would be a very complicated if not impossible task, given the quality of our data and the complexity of our econometric approach.

D. Some Illustrations of the Results

To demonstrate and discuss the main findings of the final version 4 of our model in more detail, Figures 1 and 2 are intended to give some visual impressions of the results. Figure 1 depicts the weight that the crucial independent variables firm size (S), demand expectations (Q), share of labor cost (W), and unobserved heterogeneity (ϵ) have for explaining the variability of innovative activities. On the abscissa we have drawn the observation values of these explanatory variables over their range in our data set, holding all other variables constant at their mean values, on the ordinate we have drawn the innovation probabilities. The three lines in each picture represent the probabilities that both product and process innovations (marked by circles), that only product innovations (marked by squares) and that only process innovations (marked by triangles) have been realized. It can be seen that especially firm size, demand expectations and unobserved heterogeneity have strong impacts on the variability of the innovation probabilities while wage share seems to be of minor relevance. All figures reveal that with exception of low values for ϵ , the probabilities of a simultaneous emergence of both product and process innovations are larger than the probabilities that only one innovation type is realized. This observation strengthens the assumption in our theoretical model that product and process innovations are determined by the same factors.

In order to visualize the path dependence of the innovation process, Figure 2 shows the development of the innovation probabilities for a "typical" firm which is characterized by taking mean values for all explanatory variables. We consider four different starting conditions for the initial values $Y_{-1,1}^D$, $Y_{0,1}^D$, $Y_{-1,2}^D$, $Y_{0,2}^D$. In the first version, both types of innovations were realized in both initial periods, in the last version both types were not realized, and in the remaining two versions only product or only process innovations were realized in the starting periods. All the predicted innovation probabilities converge within a few years to their long-run steady-state values (0.54 for the realization of both types of innovations, 0.16 for product innovations only, and 0.13 for process innovations only). In reality, of course, this stochastic steady-state equilibrium will never be reached, since each innovation success or failure constitutes new start conditions for the innovation process.

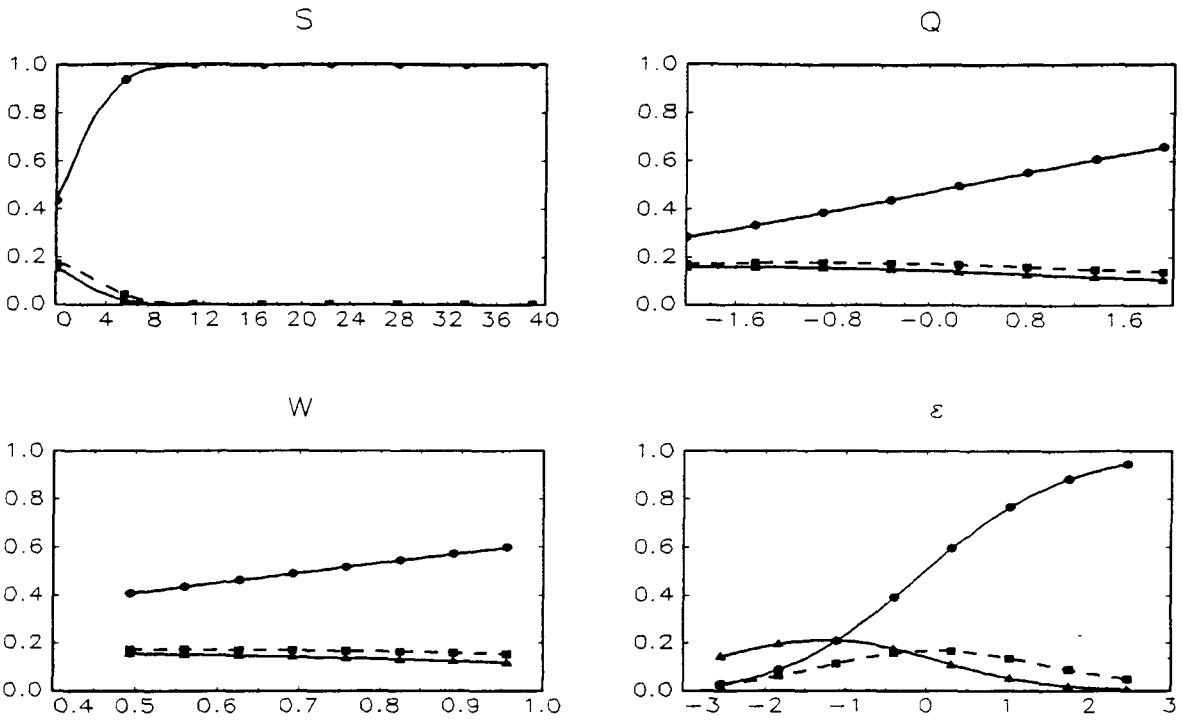


Figure 1: Importance of Some Explanatory Variables on the Variability of Innovation Probabilities

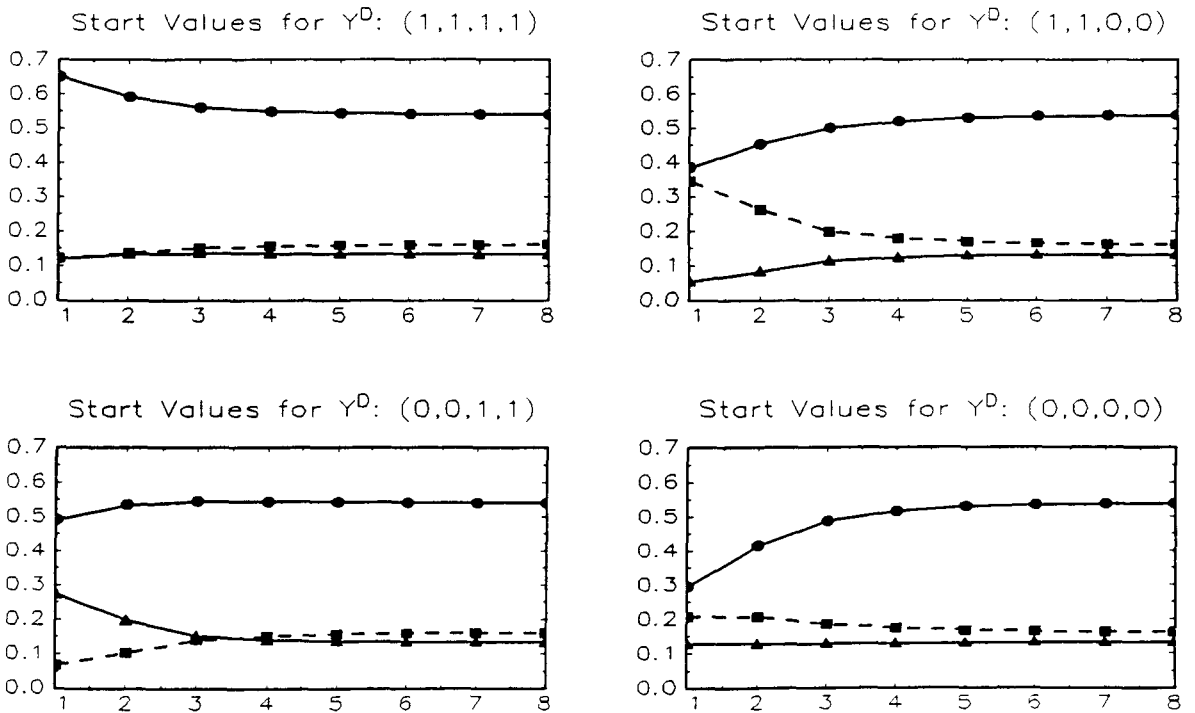


Figure 2: Dynamic Adjustment Processes for the Innovation Probabilities

6. Summary and Concluding Remarks

In this paper we developed a bivariate dynamic random effects probit model based on a theoretical model of innovation decisions of private firms. We analyzed the simultaneous dynamics of product and process innovations over time by using a panel data set of 586 firms of the West German manufacturing sector. We showed that for both types of innovation lagged realized innovations have a positive influence on the probabilities of further innovations. By accounting for random firm-specific effects we found considerably strong evidence for the importance of unobserved heterogeneity of firms. In addition, we derived a strong positive impact of the firm size on innovation success, but no significant influence of market concentration measured by the Herfindahl index. Finally, we found empirical evidence for the demand pull and the cost push hypotheses indicating more innovative activity in situations with expectations of a growing market demand and a high labor cost share.

The novel result of our study is that we found convincing evidence for dynamic spillover effects which are still neglected in the literature. These effects should not be interpreted as substitutes, but as complementary to the inter-industry and intra-industry spillover effects mentioned above. It is only the lack of adequate data in our panel that inhibits a meaningful treatment of more spillover effects (for a critical review see, e.g. Griliches 1992). For the same reason, we are not able to quantify the dynamic impacts of product and process innovations on the evolution of the market structure (see e.g. Geroski, Pomroy 1990). Nevertheless, there seems to be some correspondence to the literature on leapfrogging vs technological dominance of firms in the innovation process (see Vickers 1986). Our results indicate that successful firms will rather extend their relative technological advantage than to fall back. However, due to the stochastic formulation of our model, the advantage of successful firms does by no means ensure that technological market leaders will dominate for a long time. Whether leapfrogging has to be expected, depends not only on the random nature but also on the size of innovations. Since our data set includes only qualitative information about each firm's innovation success, we are not able to deal with such important topics like innovation rivalry between leading and lagging firms in a market. However, we have no doubt that the derived results for intra-firm spillovers and unobserved heterogeneity will continue to hold even under much more complicated circumstances for the firms' decision problems in the innovation process.

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