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On the Dynamics of Process Innovative Activity: An Empirical Investigation Using Panel Data

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by

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Abstract

This paper addresses three major aspects of firms' process innovative activity: forward-looking behaviour, uncertainty w.r.t. returns of R&D investments, and oligopolistic competition on the product market. Assuming that R&D expenditures are cost-reducing investments, we derive an Euler equation for process innovations and discuss alternative panel econometric approaches suitable to the case where only qualitative information is available. Empirical results are based on an unbalanced panel of German manufacturing firms for 1984-1989 and suggest that the Schumpeterian causality from firm size to innovation activity might in fact be attributed, at least partly, to heterogeneity in the perception of process innovative success.

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1 Introduction

Although innovative activity is by its very nature the result of a decision process of forward-looking firms operating in markets with uncertain returns, only a few empirical studies have undertaken the attempt to estimate the dynamics of the innovation process at the firm level. Most likely because of the difficulties in measuring innovative success, the vast majority of the empirical studies investigating the dynamics of innovative activity concentrates on the relationship between innovative input and intermediate innovative output as represented by patents (e.g. Hall et al. ,1986, and Hausman et al., 1984). The value of patents over their life-span is investigated by Pakes (1986) and Schankerman and Pakes (1986). While these approaches are very specific in investigating the dynamics of the transformation process from innovative input to intermediate output and in the evaluation of intermediate output, respectively, they do not explicitly model the intertemporal decision process.

A broader view of the dynamics of innovation process is taken by Hall and Hayashi (1989) who treat R&D expenditures as an investment in the firm's stock of knowledge. They adopt a strictly structural approach and derive a set of Euler equations for sales, physical capital and R&D expenditures from a dynamic investment programme and estimate these equations using data from a panel of large U.S. manufacturing firms.

The dynamics of product and process innovative output is studied in a recent paper by Flaig and Stadler (1992). They introduce a stochastic dynamic optimization model and derive equations for realized process and product innovations which are estimated using a panel probit estimator which accounts for state dependence. Since product demand and cost structure are not explicitly modelled, the estimated coefficients cannot be interpreted in terms of a structural model.

This paper is based on the idea of R&D expenditures as a cost reducing investment. This idea has been put forward in a theoretical paper by Flaherty (1980) who proves that, within a dynamic noncorporative game where firms choose output and cost-reducing investments, a stable steady state with unequal market shares exists. Our theoretical starting point is a simple model of an oligopolistic firm choosing the level of production and R&D expenditures for the current period and for every future period in order to maximize its expected present discounted value. R&D expenditures contribute to the firm's stock of technological knowledge which is assumed to be cost reducing. Although the theoretical framework of our econometric specification is extremely stylized in its assumptions and implications, it does capture three key features of innovative activity: forward-looking behaviour, uncertainty with respect to future returns, and rivalry on the product market.

By treating the R&D capital stock as a continuous variable which may be different for every firm in the market the model implies a simple notion of a realized firm-specific process innovation as any positive change of the firm's stock of R&D capital used for production. Estimates of a structural model are based on an unbalanced panel of West German manufacturing firms which contains self-reported binary information on realized process innovations. This leads to treating the change in R&D capital stock as a latent variable, the observable binary counterpart being equal to 1 if the firm reports a process innovation. Our specification draws attention to a potential measurement error in self-reported information on innovative activity as was pointed out by Kleinknecht (1987) for the case of the R&D activity measure 'labour input devoted to R&D'. We account for the possibility of systematic differences in the perception of a realized process innovation. In our model a random effect arises from unobserved heterogeneity in the firm specific thresholds to report a realized process innovation, regressors in levels correspond to observed heterogeneity in the thresholds, and regressors in first differences come from the model postulated for the latent variable. Estimates are obtained by applying a random effects probit estimator for unbalanced panels that allows for an unrestricted autocorrelation structure of the overall error term.

The paper is organized as follows: In section 2 we introduce the stochastic dynamic programming model. We discuss the specification problems that arise from an Euler equation approach if, as in our case, only qualitative information on realized process innovative activity is available. The section ends with a presentation of a structural form that can be estimated using qualitative data techniques. Section 3 describes the data and Section 4 presents the estimation results.

2 Theoretical Approach

(a) The Optimization Problem

Consider an oligopolistic firm producing a non-storable and homogeneous product and facing perfectly competitive factor markets. Let the production costs of period t be given by a constant returns to scale cost function of the following form:

(1) $$C(T_t, Z_t, w_t, q_t) = c(T_t, Z_t, w_t)q_t,$$

where q_t is the firm's output, Z_t are observable interfirm differences in production costs and w_t is a vector of factor prices. The variable T_t represents the firm's effective stock of R&D capital which is assumed to be cost reducing ($C_T < 0$) at decreasing rates ($C_{TT} > 0$). It may be interpreted as a variable capturing technological knowledge that can be accumulated over time.[1] As proposed by Griliches (1979), R&D capital has to be distinguished from the flow variable R&D expenditures, R_t. The latter are used by the firm to reduce production costs by installing process innovations. This idea is captured by the following equation:

(2) $$T_t = F_t(R_t) + (1-\delta)T_{t-1},$$

1 The terms R&D capital or accumulated knowledge should be interpreted in a broad sense so that they may include technical expertise, production secrets, patents, etc..

where $F_t(\cdot)$ is a (strictly concave) 'technology production function' and δ a redundancy rate. Since a desired level of technological progress cannot be achieved with certainty by choosing an appropriate level of R&D investment, $F_t(\cdot)$ should be thought of as a stochastic relationship between successfully installed technological knowledge and current R&D investment. For simplicity we assume that there is no gestation lag between R&D investments and R&D capital.[2]

Total demand on the product market, Q_t, is served by n oligopolistic competitors and a competitive fringe, x_t, which supplies output at marginal costs. Factor inputs can be adjusted instantaneously in every period t without adjustment costs. Given an inherited stock of technological knowledge T_{t-1} the firm's objective is to maximize its expected present discounted value $V_t(\cdot)$ by choosing the optimal level of output, technological knowledge and R&D expenditures:

(3) $$\max_{q,T,R} V_t(T_{t-1}) = \underset{t}{E} \sum_{\tau=t}^{\infty} \pi_t(q_t, T_t, R_t)\beta^{\tau-t},$$

where E_t is the expectations operator given the information set in period t. The firm's discount rate or required rate of returns is denoted by β. Let the current profit function $\pi_t(\cdot)$ be concave in all of its arguments and defined as:

(4) $$\pi_t(p_t, T_t, R_t) = [p(Q_t, D_t) - c(T_t, Z_t, w_t)]q_t - R_t,$$

where $p(\cdot)$ is the inverse of the total market demand function and D_t represents industry specific demand shift factors. Assume that uncertainty arises from future product prices, factor prices and interest rates and the uncertainty with respect to the transformation of R&D into technological knowledge. Hence $V_t(\cdot)$ can be decomposed according to

(5) $$V_t(T_{t-1}) = \pi_t(q_t, T_t, R_t) + \beta \underset{t}{E} V_{t+1}(T_t).$$

Substituting out the flow constraint (2), the first order conditions for technological knowledge are given by:

(6a) $$\frac{\partial \pi_t}{\partial T_t} + \beta E_t \frac{\partial V_{t+1}}{\partial T_t} = 0$$

(6b) $$\frac{\partial V_t}{\partial T_{t-1}} = \frac{\partial \pi_t}{\partial T_{t-1}}.$$

2 Hall and Hayashi (1989) introduce a gestation lag by assuming that effective R&D capital stock has an impact on profits realised in the future period $t + \tau$.

The Euler equation representation is obtained by taking (6*b*) one period ahead and substituting in (6*a*):

(7) $$\frac{\partial \pi_t}{\partial T_t} + \beta \frac{\partial \pi_{t+1}}{\partial T_t} + u_{t+1} = 0,$$

where u_{t+1} is the usual rational expectations error with $E_t(u_{t+1}) = 0$. In addition to the Euler equation, the first order condition with respect to output has to be satisfied for every period t:

(8) $$p_t(1 - m_t) - c(T_t, Z_t, w_t) = 0$$

where $$m_t \equiv -\frac{\partial p_t}{\partial q_t}\frac{q_t}{p_t}.$$

Equation (8) is the familiar equality between marginal revenue and marginal costs and m_t is the relative price response of the market to an output change of the oligopolist, and corresponds to the mark-up of prices over marginal costs.

Econometric specifications for process innovations that are solely based on equation (8) reveal two interesting properties: Contrary to the Euler equation (7) the first order condition given by (8) is purely static and contains only information of the current period. Thus, although the model is dynamic in essence, a subset of the parameters can be estimated without imposing possibly strong restrictions on the initial conditions of the process. This turns out to be necessary if only qualitative information on the dependent variable is available, as in our data set. Interesting information on the dynamics of the process is neglected. This includes transformation process of R&D into innovative success, the redundancy rate and the firm's discount rate. However, if the major interest lies in the estimation of the relationship between innovative success and the market structure, the first order conditions with respect to output capture all available information on the firm's pricing behaviour.

(b) Towards an Empirical Implementation

Although the Euler specification given by equation (7) is fairly standard and looks similar to dynamic models for factor demand in a neo-classical framework (e.g. Machin, Manning, Meghir 1991), the econometric implementation of (7) using a specific parametric specification is far from being straightforward due to the qualitative nature of the dependent variable. To clarify this point assume for the inverse of (2) the simple quadratic form:

(9) $$R_t = \frac{\gamma}{2}[T_t - (1 - \delta)T_{t-1}]^2.$$

With the above profit function (4), the Euler equation (7) yields, after solving for T_{t+1}:

(10) $$T_{t+1}=\frac{\beta(1-\delta)^2+1}{\beta(1-\delta)}T_t-\frac{1}{\beta}T_{t-1}+\frac{c_T(t)q_t}{\beta(1-\delta)\gamma}+v_{t+1}$$

where: $$c_T(t)=\frac{\partial c(T_t,Z_t,w_t)}{\partial T_t}; \qquad v_{t+1}=-\frac{1}{\beta(1-\delta)\gamma}u_{t+1}.$$

In its general form, the dynamic equation given by (10) is hardly of any use for applied econometric work, since the endogenous variable is not measurable and its lagged value enters the equation in a nonlinear fashion through the marginal costs of technological change.

Our econometric work is based on the assumption of an isoelastic total demand curve of the form

(11) $$p_t=\exp(\varepsilon_0 D_t)Q_t^{-\frac{1}{\varepsilon}}, \qquad \varepsilon,\varepsilon_0>0.$$

Assuming quantity Cournot behaviour for the oligopolists and a constant supply elasticity $\eta(>0)$ for the competitive fringe, the relative response of the price to an output change of firm i is given by:

(12) $$m_{it}=\frac{1}{\varepsilon+\eta(1-K_t)}S_{it},$$

where $S_{it}\equiv q_{it}/Q_t$ is the relative size of the firm i and K_t is the n-firm concentration ratio. Finally, let the cost function be of the form:

(13) $$C(T_{it},Z_{it},w_{it})q_{it}=\exp(-\alpha_1 T_{it})Z_{it}^{\alpha_2}w_t^{\alpha_3}q_{it}$$

with all parameters $\alpha_j(j=1,2,3)$ being positive. With these assumptions and two specific linear approximations (see the appendix for the derivation), the first order conditions with respect to output (8) solved for T_{it} yield a static behavioural equation that relates the level of technology to output and market structure variables:

(14) $$T_{it}=const_t+\frac{1}{\alpha_1\varepsilon}\ln Q_t-\frac{\varepsilon_0}{\alpha_1}\ln D_t+\frac{1}{\alpha_1\varepsilon}S_{it}$$
$$-\frac{\eta}{\alpha_2\varepsilon^2}(1-K_t)S_{it}+\frac{\alpha_2}{\alpha_1}\ln Z_{it}+\frac{\alpha_3}{\alpha_1}\ln w_t,$$

where the time dependence of the constant term may arise from disembodied technical change (not explicitly modelled here) as well as from cost and demand shocks common to all firms in the sample. A similar relationship also based on first order conditions for output has been used by König and Pohlmeier (1992) and Laisney, Lechner and Pohlmeier (1992).

Contrary to these studies and the study of Flaig and Stadler (1992) we define a realized process innovation of a firm as a (positive) change in technological knowledge. According to this interpretation a process innovation of the i-th firm takes place if the latent variable $I_{it}^{*} = T_{it} - T_{i,t-1}$ is positive. In terms of this variable the Euler equation (10) becomes (see the appendix):

$$(15) \qquad I_{i,t+1}^{*} = const + \theta_1 I_{it}^{*} + \beta_1 p_t q_t (1 - m_{it}) + \beta_2 \ln Q_{t-1} + \beta_3 \ln D_{t-1} + \beta_4 S_{i,t-1} + \beta_5 (1 - K_{t-1}) S_{i,t-1} + \beta_6 \ln Z_{i,t-1} + \beta_7 \ln w_{t-1} + v_{i,t+1}.$$

Our assumption about the pricing behaviour and the parametric form of the demand and the cost function imply that β_1, β_3, and β_5 should be negative, while the other coefficients should be positive (see the appendix). The Euler equation approach is not affected by the Lucas critique since (15) contains only variables of the sample period. This is in contrast with forward solution methods that require out-of-sample predictions of the expected future marginal contribution of a technology change to profits (e.g. Flaig and Stadler, 1992).

Although the right hand side of (15) only contains predetermined variables, an interpretation of the dynamics of process innovations calls for extreme caution since market size, relative firm size, price and price-cost markups are clearly endogenous. Thus a change of an exogenous factor in $t-1$ (e.g. a cost push via $Z_{i,t-1}$) has a direct impact on process innovations two periods ahead but also causes an indirect effect through the subsequent change in the market structure. Finally, there will be a long run effect on process innovations through the autoregressive part of the equation (15).

The coefficient on lagged process innovations being positive, one could argue that our specification is compatible with the "success breeds success" hypothesis as discussed by Mansfield (1968) and Stoneman (1983). This argumentation, however, rests on the idea that innovative success confers advantages in technological opportunities that make success more likely. In our model the positive effect of lagged process innovations on current innovations simply results from a costly adjustment to the optimal technological level by means of R&D investment.

Since our data includes information on a firm's realized process innovations in the form of a binary variable only, equation (15) defines a dynamic version of a threshold crossing binary choice model. Due to the existence of the lagged latent dependent variable estimating such an equation is far from trivial.

Lechner (1991) proposes an estimation strategy for that type of models. However, his estimator is only consistent if (i) an explicit initial condition is specified and (ii) if the regressors are strictly exogenous. Although the equation for the initial condition can be specified in a fairly general way by allowing for regressors and an arbitrary correlation of its error term with the error terms of the subsequent periods, it should not contain a lagged dependent variable. In empirical work this assumption may not be too restrictive, if the effect of a lagged dependent variable in the initial condition can be approximated by using lags of the time varying explanatory variables. Unfortunately, we do not have access to these variables without reducing the sample size considerably. Moreover, the assumption of strict exogeneity of the regressors in that dataset has been discussed by Laisney, Lechner und Pohlmeier (1992) in the context of a correlated random effects model, and shown to be hardly tenable. Given these considerations we refrain from the estimation of a 'truly' dynamic model at this stage of our research, since the results could not be reasonably interpreted in our context, due to the violation of important assumptions.

Flaig and Stadler (1992) suggest the use of a model with the observed (dummy) lagged dependent variable instead of a latent lagged dependent variable (as suggested by theory) as regressor. However, although they invoke much more stringent assumptions on the joint distribution of the error terms over time, their estimation is subject to the inconsistency problems described above.

(c) A Simple Alternative

Using an Euler equation approach as sketched above allows the econometrician to obtain estimates of the dynamics of the process. As was pointed out earlier, a first difference version of (14) is sufficient, if the major interest lies in the impact of market structure variables on innovation:

(16)
$$I_{it}^{*} = \Delta const_t + \frac{1}{\alpha_1 \varepsilon} \Delta \ln Q_t - \frac{\varepsilon_0}{\alpha_1} \Delta \ln D_t + \frac{1}{\alpha_1 \varepsilon} \Delta S_{it} - \frac{\eta}{\alpha_1 \varepsilon^2} \Delta (1 - K_t) S_{it} + \frac{\alpha_2}{\alpha_1} \Delta \ln Z_{it} + \frac{\alpha_3}{\alpha_1} \Delta \ln w_t .$$

For the binary information of the Ifo business survey, (16) defines the latent form of a panel probit model. In the empirical application we use self-reported realized process innovations as the observable dependent variable. Using Dutch data Kleinknecht (1987) reports for the input measure 'man devoted to R&D' a considerable downward bias for small firms. He argues that in small firms R&D is a mixed activity. Hence firms having no R&D department or explicit R&D budget are likely to underreport their innovative input. A similar argument may hold for measures of innovative output. Moreover, it is likely that firms have different perceptions regarding a realized process innovation. Thus we assume that the observable binary variable I_{it} takes on the value 1 (= the firm has realized a process innovation) if its continuous latent counterpart I_{it}^{*} has crossed a firm specific threshold τ_{it}:

(17)
$$I_{it} = \begin{cases} 1 \text{ if } I_{it}^{*} > \tau_{it}, \\ 0 \text{ otherwise }, \end{cases}$$

and endogenize the threshold parameter by expressing τ_{it} as a linear function of observable characteristics W_{it} a normally distributed random component u_{it} with unconstrained intertemporal covariance matrix (this nests the standard error components specification):

$$\tau_{it} = -W_{it}\theta + u_{it}. \qquad (18)$$

Of course, economic theory does not give any advice as to which explanatory variable should belong to the vector of variables explaining the threshold. Potential candidates could be firm size and industry specific dummies. Since specification (16) is set up in first differences, there is no problem in identifying the parameters of the innovation equation from the parameters of the threshold equation.

3 Data

The empirical analysis is based on a seven-wave unbalanced panel of West German firms from the Ifo business survey "Konjunkturtest" for 1983-1989, using the specific questions asked yearly regarding innovation behaviour. Given that our specification requires first differences for some of the regressors, we will lose most of the information contained in the 1983 wave. The indicator for process innovation, denoted *IC*, corresponds to the positive assertion "for product *X* we have realized process innovations in the year *Y*" (see Oppenländer and Poser, 1989, p. 269).

From Table A.1 in the appendix, which displays summary statistics, one can see that the proportion of firms recording process innovation in a given year varies between 46.8% in 1985 to 55.2% in 1989. As already mentioned in the study of Laisney, Lechner und Pohlmeier (1992), the "firms" considered in the panel are "one-product-firms" (OPF) defined within each plant in such a way that they produce a single good at the two-digit level in the nomenclature of the Federal Statistical Office (Statistisches Bundesamt). For each OPF we know both the employment at the product level *EMPLP* and at the company level *EMPLC*[3]. Data at the two-digit industry level obtained from the German Statistical Year-books 1986-1990 and the German Monopolkommission (1985/1986, 1987/1988 and 1989/1990) give us the industry employment *EB*, the industry value added *QB* (expressed in millions of current[4] DM) and the share of the six largest firms in total industry sales *C6*. From these raw data we construct variable *SP=EMPLP/EB*, our measure of the relative size of the firm. The Table also gives information on *SC=EMPLP/EMPLC*, which should help capture the economies of scale of multiproduct plants in process innovation. We use this information in the form of

3 The large increase in the average number of company employees between 1986 and 1987 is mainly due to an outlier.

4 The inflation rate over the period considered was so small that no deflation was necessary. Since *QB* is the only nominal variable used, and it appears in log-linear form in the model, time dummies would take care of inflation effects anyway.

two dummies: $SC8=1 \Leftrightarrow SC>0.8$ indicates firms where such economies of scale are almost non-existent, and $SC2=1 \Leftrightarrow SC<0.2$ indicates firms where they are greatest. Thus we would have expected $SC8=1$ ($SC2=1$) to reduce (increase) the probability of process innovation, other things being equal. However, no such effect appeared to be present.

Different variables in the data set depict long run demand expectations. We use these variables as indicating perception of relative cost advantages and include them in the variable set D. Alternatively, one could rationalize these as revealing heterogeneity in the demand elasticity ε. The proportion of one-product-firms with the best prospects ranges from 2.9% in 1987 to 7% in 1989. The proportion of those with merely positive expectations ranges between 38% in 1987 and 60% in 1989. For merely negative expectations the range is 5% (1989) to 13.5% (1987), and for strongly negative expectations 2.7% (1986 and 1987) and 0.5% (1989). We also consider the change in these expectations. This is positive for a proportion of firms ranging between 17.4% (for 1987/1986) to 29.6% (for 1987/1988) and negative for a proportion between 22.6% (1987/1986) and 10.1% (1989/1988).

Other variables considered in the analysis are the export share of the industry, *EXPS*[5], and a dummy indicating non exporting firms, *NEF*, both considered as candidates for variable set D, as proxies for the relative competitiveness on the world market, and the average hourly wage rate in the industry. Finally we consider four sectoral dummies G (raw materials), I (investment goods), N (foods), C (other consumption goods), in order to capture further observable heterogeneity.

4 Results

For the estimation of equations (16) and (18), respectively, we apply Chamberlain's (1984) $\Pi-$ Matrix approach for panel probit models. Since (16) is specified in first differences heterogeneity across firms and industries affecting the structural equation through an individual fixed or (possibly correlated) random effect is eliminated. The only heterogeneity that remains results from the threshold parameter which is by assumption of an uncorrelated error components type. This allows us to apply the Chamberlain approach using unbalanced panel data provided that observations are randomly missing (see Laisney et al., 1993, for the derivation). Accounting for the unbalanced nature of the Ifo-data increases the number of observations that can be used for our estimations from 5142 (= 857 per wave) for the balanced panel to 11923 observations (= 1987 on average per wave). In addition, the Chamberlain approach allows for a general covariance structure of the overall error term $v_i + u_{it}$.

5 The study of Laisney et al. (1992) makes use of the more doubtful variable "import share".

Since the estimation method applied in the second stage is minimum distance it provides a statistic which indicates how well the imposed restrictions on the estimated coefficients from the cross-section estimates (first stage estimates) hold. Thus the distance statistic points to the lack of stability of the cross section estimates which is documented by Mairesse and Griliches (1990) for the case of production functions estimated on firm level data.

Table 1 shows two sets of estimation results differing only according to the inclusion of the relative firm size, *SP*, as an additional variable in the threshold. In the latter specification we assume that the perception of a realized process innovation depends on the size of the firm and hence varies over time while in the first specification we assume for identification that a firm's perception is time independent aside from the pure 'white noise' error term. For both specifications the restrictions imposed by minimum distance in the second stage cannot be rejected, indicating that the stability of coefficients across time does not seem to be a specification problem.

The change in concentration ratio reveals a significantly negative impact on process innovative activity in the first specification. However, if (the level of) relative firm size *SP* is included, the hypothesis of no significant impact can no longer be rejected. This finding is in accordance with numerous other empirical studies based on different data sources, estimation techniques and definitions of the dependent variable that lead Cohen and Levin (1989, p.1078) to conclude that the effects of firm size and concentration (on innovative activity), if they appear at all, do not appear to be important. The equality of the coefficients on relative firm size and market size that arises in our model cannot be rejected. Regardless whether this parametric restriction is imposed or not, there is no evidence that market size and relative firm size significantly explain differences in process innovative activity.[6]

Interpreting the level of relative firm size as a threshold explaining variable the significantly positive coefficient supports the findings of Kleinknecht (1987) for innovative input. Large firms reveal a lower threshold to report realized process innovations and thus are more likely to report an innovation. What looks like a Schumpeterian causality on the first glance might thus boil down to a perception effect.

Like in many other econometric studies using the Ifo business survey, demand expectations offer the largest explanatory power for (self-reported) realized process innovations. Firms reporting the best demand prospects are most innovative while firms with negative long run demand expectations reveal significantly lower innovative activity. Interestingly, firms which have faced an improvement in demand expectations from the last to the current period are less likely to innovate than firms with stable

6 The studies by Flaig and Stadler (1992) and Laisney et al. (1992) which adopt a different interpretation of the dependent variable find a significant impact of relative firm size on process innovations. This also holds for Pohlmeier (1992) who reports a significant effect of relative firm size and total market size.

Table 1 Random Effects Panel Probit estimates

Variable	coeff.	(t-val)	coeff.	(t-val)
Variables in β				
$\Delta[SP + \ln QB]$	-.248	(-.6)	.074	(.2)
$\Delta[(1-C6)SP]$	36.7	(3.4)	14.0	(1.1)
Δexport share	-2.07	(-1.7)	-2.43	(-2.0)
demand expectations:				
strong increase	.904	(8.4)	.838	(8.0)
increase	.476	(8.7)	.451	(8.5)
decrease	-.167	(-2.8)	-.157	(-2.7)
strong decrease	-.301	(-2.3)	-.272	(-2.2)
positive change	-.140	(-3.8)	-.004	(-.1)
negative change	-.004	(-.1)	-.124	(-3.5)
Variables in θ				
SP			14.9	(4.1)
non-exporting firm (*NEF*)	-.202	(-2.5)	-.187	(-2.4)
raw materials (*G*)	-.041	(-.4)	-.103	(-1.0)
investment goods (*I*)	.302	(3.2)	.265	(2.9)
consumption goods (*C*)	.221	(2.3)	.198	(2.1)
Northern States	.002	(.0)	-.025	(-.3)
Northrhine-Westphalia	-.073	(-1.0)	-.071	(-1.1)
Bavaria, Baden-Württemberg	-.037	(-.6)	-.037	(-.6)
Time effects				
intercept 1984	-.371	(-3.2)	-.367	(-3.3)
intercept 1985	-.416	(-3.6)	-.411	(-3.7)
intercept 1986	-.290	(-2.6)	-.297	(-2.8)
intercept 1987	-.289	(-2.6)	-.294	(-2.7)
intercept 1988	-.261	(-2.3)	-.272	(-2.5)
intercept 1989	-.296	(-2.6)	-.301	(-2.7)
Relative precisions[7]				
α_{1984}	.721	(2.7)	.804	(1.8)
α_{1985}	.838	(1.4)	.888	(1.0)
α_{1986}	.888	(1.0)	.888	(1.0)
α_{1987}	.789	(1.9)	.807	(1.6)
α_{1988}	.926	(.6)	.973	(.2)
α_{1989}	1.000		1.000	(.0)
χ^2		83.0		101.0
d.o.f.		75		80
empirical significance in %		24.68		5.61

7 t-values for $H_0 : \alpha_t = 1$, with $\alpha_t = \sigma_T / \sigma_t$

positive demand expectations. To some extent the latter finding can be interpreted as evidence for the long run character of investment in R&D capital that slowly adjusts to improved market conditions.

In our theoretical framework demand shift factors as given by the variable D reduce the firm's incentive to innovate, since, ceteris paribus, higher marginal revenues go along with higher marginal costs and thus with a lower level in the R&D capital stock. If the sectoral export share proxies industry-specific demand conditions with a higher export indicating better demand conditions, the negative, but only weakly determined coefficient on the change in the sectoral export share has the theoretically expected sign.

This has to be distinguished from the effect of the firm specific dummy variable *NEF*, which takes the value one if the firm does not operate on the export market. The negative coefficient is in accordance with intuition in the sense that firms which are not competing in international markets are less likely to realize process innovations. However, interpreting *NEF* as influencing the threshold would mean that non-exporting firms have a higher threshold for reporting process innovations. Since the first line of argumentation appears to be more convincing the variable is likely to pick up firm and sectoral specific differences that have not been properly accounted for.

A similar argument holds for the sign pattern of the remaining estimated coefficients of the threshold function which seems counterintuitive as well. If the impact of the explanatory variables is interpreted in terms of the threshold function we have to conclude that firms producing investment goods or consumption goods (positive coefficient) have a lower threshold to report realizations of process innovations than firms belonging to the food industry which serves as our reference category. Again, a more reasonable interpretation of this finding may be that the industry dummies pick up structural differences in cost and demand conditions. This suggests that sectoral studies might be rewarding.

5 Conclusions

In this paper we undertake the attempt to model process innovative behaviour in a world of forward-looking oligopolistic firms with uncertainty. We derive two different structural equations that relate process innovations to market structure variables and cost shift factors. Due to the qualitative nature of our dependent variable we estimate in a first step a structural form that is based on the first order conditions for output.

Our estimation results are not fully in accordance with the findings of previous studies using the same data source. Market concentration reveals a significantly negative or an insignificant impact on process innovative activity depending on the specification being used. We do not find any significant impact of a change in market size and relative firm size on innovations. As in many other econometric studies using the Ifo business survey demand expectations offer the largest explanatory power for (self-reported) realized process innovations.

Blaming the quality of the data seems to be an obvious excuse since the regressors used are far from being good proxies of the true variables our model calls for. Considering, however, the respectable size of the sample in the cross-sectional dimension and (to a lesser degree) in the time series dimension, the findings deserve some attention despite the quality of the variables being used.

So far we have not yet accounted for endogeneity of the various output measures. The study by Pohlmeier (1992) based on cross sectional data shows that parameter estimates can be seriously biased (and may even change signs) if the simultaneity of innovations and market structure is not properly accounted for. Two different econometric approaches seem feasible: (i) the generalized method of moments approach by exploiting the panel structure of the data or (ii) a simultaneous probit technique applied to the cross sections combined with a minimum distance approach in the second stage of the estimation process to impose the panel structure on the coefficients. The first approach requires the existence of a set of suitable internal instruments, which necessitates some restriction on the autocorrelation structure of the residuals. The second approach requires the existence of a set of suitable external instruments. This is problematic in two respects: on theoretical grounds, the very existence of such instruments can be questioned (see Schmalensee, 1989), and on practical grounds, the data set we use contains very few variables.

As a by-product, our theoretical approach draws attention to a serious identification problem inherent in econometric models using self-reported innovative activity as dependent variable, particularly, if they are set up in levels (e.g. models estimated on cross-sections) rather than in first differences.

Firm size effects have to be interpreted with extreme caution since they may not capture the old Schumpeterian story but a simple perception effect or measurement error due to the construction of the dependent variable. What is interpreted in cross-section studies as a firm size effect might simply reflect at least to some extent the possibility that large firms are more likely to report an innovation. With respect to the industry specific differences our results do not clearly point out that there are systematic differences in the perception of a realized process innovation. It seems more plausible that industry dummies pick up structural heterogeneity. Nevertheless this point deserves more attention in future research.

Appendix: Derivation of Equations (14) and (15) and descriptive statistics

Assuming a cost function given by equation (13) and solving (8) for T yields for the i-th oligopolist.

$$T_{it} = -\frac{1}{\alpha_1}\ln p_t + \frac{1}{\alpha_1}m_{it} + \frac{\alpha_2}{\alpha_1}\ln Z_{it} + \frac{\alpha_3}{\alpha_1}\ln w_t, \qquad (A1)$$

where we use the approximation $\ln(1-m) \approx -m$.

For an iso-elastic demand function and quantity Cournot behaviour the price-cost markup for the i-th oligopolist is:

$$(A2) \qquad m_{it} = \frac{1}{\varepsilon + \eta(1-K_t)} S_{it}$$

where

$$S_{it} = \frac{q_{it}}{Q_t}; \qquad K_t = \frac{Q_t - x_t}{Q_t}; \qquad \eta = \frac{\partial x_t}{\partial p_t}\frac{p_t}{x_t}; \qquad \varepsilon = \frac{\partial Q_t}{\partial p_t}\frac{p_t}{Q_t}.$$

Since expression (A2) is nonlinear in the parameters η (supply elasticity of the competitive fringe) and ε (price elasticity of with respect to total demand) as well as in the variables S_{it} (relative firm size) and K_t (n-firm concentration ratio) we adopt the approximation[8]:

$$(A3) \qquad m_{it} \approx \frac{1}{\varepsilon} S_{it} - \frac{\eta}{\varepsilon^2}(1-K_t)S_{it}.$$

Inserting this into (A1) while using (11) yields equation (14).

The Euler equation (10) can be expressed in terms of process innovations by subtracting T_t from both sides which yields after collecting terms (and dropping subscript i for a moment):

$$(A4) \qquad I^*_{t+1} = \theta_1 I^*_t + \theta_2 T_{t-1} + \theta_3 c_T(t) q_t + v_{t+1},$$

with:

$$\theta_1 \equiv \frac{1-\beta\delta(1-\delta)}{\beta(1-\delta)} > 1,$$

$$\theta_2 \equiv \frac{\delta(1-\beta(1-\delta))}{\beta(1-\delta)} > 0, \qquad \theta_2 < \theta_1,$$

$$\theta_3 \equiv \frac{1}{\beta(1-\delta)\gamma} > 0.$$

Substituting (14) for $t-1$ in $(A4)$ and using the relationship $c_T(t)q_t = -\alpha_1 c(t) q_t = -\alpha_1 p_t q_t (1-m_t)$ we obtain equation (15), where

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8 This step uses the approximation formula $1/(a+x) \approx 1/a - x/a^2$ for small x , see Bronstein and Semendjajew (1982, p. 101) for the evaluation of the approximation error.

$$(A5) \qquad \beta_1 \equiv -\theta_3 \cdot \alpha_1 = -\frac{\alpha_1}{\beta(1-\delta)\gamma} < 0$$

$$\beta_2 = \theta_2 \cdot \frac{1}{\alpha_1 \varepsilon} = \frac{\delta(1-\beta(1-\delta))}{\alpha_1 \varepsilon \beta(1-\delta)} > 0$$

$$\beta_3 = -\theta_2 \frac{\varepsilon_0}{\alpha_1} = -\frac{\varepsilon_0 \delta(1-\beta(1-\delta))}{\alpha_1 \beta(1-\delta)} < 0$$

$$\beta_4 = \theta_2 \frac{1}{\alpha_1 \varepsilon} = \beta_2 > 0$$

$$\beta_5 = -\theta_2 \frac{\eta}{\alpha_1 \varepsilon^2} = -\frac{\eta \delta(1-\beta(1-\delta))}{\alpha_1 \varepsilon^2 \beta(1-\delta)} < 0$$

$$\beta_6 = \theta_2 \frac{\alpha_2}{\alpha_1} = \frac{\alpha_2 \delta(1-\beta(1-\delta))}{\alpha_1 \beta(1-\delta)} > 0$$

$$\beta_7 = \theta_2 \frac{\alpha_3}{\alpha_1} = \frac{\alpha_3 \delta(1-\beta(1-\delta))}{\alpha_1 \beta(1-\delta)} > 0.$$

Table A.1: Descriptive Statistics

Variable	Description	Mean					
		1984	1985	1986	1987	1988	1989
IC	Process innovation realized (dummy)	.479	.468	.512	.509	.538	.552
EMPLP	OPF employment (number of employees)	467	470	536	538	549	548
EMPLC	Firm employment (number of employees)	2,686	2,930	3,308	3,426	3,511	3,230
SP	Relative size (EMPLP/Industry employment)	.002	.002	.003	.002	.003	.003
DET1	Strongly increasing total demand expectations	.037	.035	.032	.029	.042	.070
DET2	Increasing total demand expectations	.393	.407	.415	.382	.508	.598
DET4	Decreasing total demand expectations	.116	.108	.111	.135	.081	.051
DET5	Strongly decreasing total demand expectations	.027	.020	.027	.027	.020	.005
DDETP	Positive change in total demand expectations	.189	.211	.175	.174	.296	.262
DDETM	Negative change in total demand expectations	.211	.194	.211	.226	.112	.101
SC	Share of OPF in firm employment (EMPLP/EMPLC)	.603	.592	.645	.650	.653	.658
SC2	OPF small vs. firm (dummy SC<0.2)	.150	.147	.147	.155	.156	.154
SC8	OPF large vs. firm (dummy SC>0.8)	.343	.316	.441	.454	.456	.468
lnQB	Logarithm of industry value added[9]	9.97	10.09	10.14	10.20	10.26	10.36
C6	Share of 6 largest firms in industry sales	.211	.215	.205	.204	.211	.204
EXPS	Export share in industry output	.286	.295	.299	.296	.301	.306
G	Sector raw materials (dummy)	.108	.109	.120	.106	.112	.117
I	Sector investment goods (dummy)	.476	.493	.484	.494	.498	.488
N	Sector foods (dummy)	.051	.050	.049	.047	.049	.054
C	Sector other consumption goods (dummy)	.365	.348	.347	.353	.342	.342
NORD	Northern states	.121	.117	.115	.113	.120	.116
NRW	Northrhine-Westphalia	.287	.299	.302	.300	.296	.291
BAYBAWÜ	Bavaria or Baden-Württemberg	.486	.478	.471	.475	.468	.478
NEF	Non exporting firm	.040	.040	.047	.051	.051	.058
obs	Number of observations	2276	2191	2066	1843	1789	1758

9 With QB in millions of current DM; at the two-digit industry level of Statistical Year-books.

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