Discussion Paper No. 01-39

Innovation Dynamics and Endogenous Market Structure

Econometric Results from Aggregated Survey Data

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Non–technical Summary

The effect of market structure on innovative activity has been one of the main topics of empirical industrial economics. But, in most of the studies the feedback effect of innovation on market structure is neglected, at least in the empirical analysis. This paper analyzes the interdependency between innovation and market structure for German manufacturing industries in the nineties.

We use a newly constructed panel data set which results from expanding firm level data on innovative activity (Mannheim Innovation Panel, MIP) on the sectoral level of aggregation. This data set has been merged with publically available data from the German statistical office. Innovative activity is measured by the share of R&D expenditure in total sales and market concetration by the Herfindahl index of sales concentration.

For the German manufacturing sector, innovative activity leads to more concentrated markets in the long run, and hence to greater market power of firms reducing competition. On the other hand, competition enforces innovation. Firms engage in R&D to withstand competitive pressure. Competition is a fundamental incentive for innovation.

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Econometric Results from Aggregated Survey Data

by

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July 5, 2001

Abstract: This paper examines empirically the relationship between innovation and market structure within a simultaneous framework at the industry level of aggregation. We use a model in which R&D affects both, demand and cost conditions. An optimization process leads to optimal industry R&D expenditure and market structure in a symmetric equilibrium. The model is applied to a newly constructed panel for Germany. Generalized Method of Moments (GMM) estimation techniques for dynamic panel data systems are used to estimate the parameters of interest. We found a positive long–run effect of R&D on markets' sales concentration. In contrast, competition enforces innovation, i.e. sales concentration has a negative impact on R&D.

Keywords: innovation, R&D, market structure, panel data, dynamic models, applied econometrics

JEL Classification: O31, L11, C33, L60

Acknowledgements The authors would like to thank Georg Licht for helpful comments and their colleagues Thorsten Doherr, Günther Ebling, Thomas Hempell, Hiltrud Niggemann and Bettina Peters for sharing the load of preparing the data set.

1 Introduction

It has been a central issue of industrial economics how differences in market structures affect economic performance. A common argument in this context is that concentrated markets may be favorable to technological progress, and hence economic growth. This issue was brought into mainstream economics by Schumpeter (1942), who argued that large firms operating in concentrated markets are the main engine of technological progress. A number of specific hypotheses as to why this may be the case have been advanced. For instance, innovation may be higher in concentrated industries because firms with greater market power have better access to resources for financing research and development (R&D). Moreover, they can more easily appropriate the returns from innovation and hence have more incentives to innovate because of internal capabilities. In contrast to the Schumpeterian hypotheses, Scherer (1967) states that firms in a fully competitive market are more likely to innovate. The pressure of competition encourages innovation activities for staying in the market in the long–run. Market power based on absence of strong competitive pressure possibly leads to inertia.

The theoretical literature has emphasized that both innovation and market structure are endogenous (see e.g. Dasgupta and Stiglitz, 1980, Futia, 1980, Lee and Wilde, 1980). Dasgupta and Stiglitz (1980) argue that in the short run market structure and innovation are determined simultaneously. The degree of concentration in an industry ought not be treated as given. They do not regard the relationship between concentration and innovative activity as a causal one. Whereas Futia (1980) states that industries with greater innovative opportunities tend to be more concentrated.

Many empirical studies concerning the relationship between innovation and market structure have used single equation models to relate some measure of innovative inputs or output to some concentration indices. A serious problem with this approach is the obvious endogeneity of market concentration (for an overview see Cohen and Levin, 1989 and Cohen, 1995). Among the models that have focused on the relationship between cost-reducing and demand-creating R&D on the one hand and market structure on the other hand are: Levin and Reiss (1988) and Harhoff (1997), whereas other models are limited on cost-reducing R&D, see e.g. Dasgupta and Stiglitz (1980) as well as Levin and Reiss (1984).

We use the model developed by Levin and Reiss (1988) in which firms perform cost-reducing process and demand-creating or price increasing product R&D. It yields a number of important insights into relationships between R&D spillovers, technological opportunities, and market structure. The effect of spillover on the amount and composition of R&D can be examined. However, in their empirical implementation Levin and Reiss (1988) restricted their analysis to cross section data. Moreover, they only use a single equation estimation approach for both, the resulting market concentration equation and the R&D equation.

We extend the analysis of Levin and Reiss (1988) in two directions: firstly, we explicitly consider the simultaneity of market structure and R&D expenditure in the estimation framework. Secondly, we use panel data, which allow for incorporating dynamic aspects of the market structure–R&D relationship by including lagged variables. We use generalized method of moments (GMM) estimation techniques for dynamic panel data systems to consider the interdependence of the endogenous variables. The data originate from a new data set for Germany which was constructed from the Mannheim Innovation Panel (MIP) by expanding relevant variables to industry levels.

The outline of the paper is as follows. The model of Levin and Reiss (1988) is sketched in the following second chapter. Chapter 3 contains the empirical specification where deviations from Levin and Reiss (1988) are explained in detail. In chapter 4 we briefly introduce the estimation technique. Estimation results and interpretations follow in chapter 5. Chapter 6 concludes and outlines directions for future research.

2 The Theoretical Model

Market structure, i.e. the number and size distribution of firms, is determined by demand and cost conditions which firms' are facing within the industry. Demand and cost conditions change if firms invest in R&D to improve production processes and renew products. But firms' decisions on R&D expenditure depend on market structure as well as on appropriability conditions. Hence, market structure and R&D activity are interdependent.

We follow Levin and Reiss (1988) to model the interdependence between market structure and innovation. According to Levin and Reiss (1988), firms spend money on R&D to perform process as well as product innovation which have different impacts on the firms' demand and cost conditions. Process innovations reduce the production costs per unit while product innovation widen the scope of pricing. Hence, R&D expenditure on process innovations (*process R&D*) is cost decreasing and R&D expenditure on product innovation (*product R&D*) is price increasing or demand creating.[1] Since firms within an industry more or less act on the same sales and purchasing markets and possibly cannot completely appropriate the returns on their R&D due to spillovers, firms decisions are interdependent. Levin and Reiss (1988) apply the Cournot–Nash–conjecture to model the interdependence of profit–maximizing firms. The outcome determines the equilibrium scale of R&D expenditure and equilibrium number of firms within an industry.

Firms' production possibilities are affected by own as well as by pooled industry process R&D. Own R&D contributes to both, firms' individual as well as pooled industry knowledge. Own and rival process R&D are considered as perfect substitutes in the pool of industry knowledge. Following Levin and Reiss (1988), the unit cost function of firm i can be defined as[2]

$$C_i = C(r_i, \bar{r}_i) = A_c r_i^{-\alpha_r} \bar{r}_i^{-\gamma_r}, \quad (i = 1, ..., N) \tag{1}$$

which is a Cobb–Douglas function in r_i, the quantity of own process R&D done by firm i, and $\bar{r}_i$ the pool of industry knowledge available to firm i with

$$\bar{r}_i = r_i + \omega_r \sum_{j \neq i}^{N} r_j. \tag{2}$$

ω_r is a scalar parameter representing the extent of process R&D spillovers, i.e. the extent to which other firms' process R&D contribute to the pool of knowledge available to firm i. The parameter γ_r, the elasticity of unit cost with respect to the industry R&D pool, is representing the productivity of spillover in contrast to their extent. α_r defines the elasticity of unit cost with respect to own R&D in the

[1]In practice, product and process innovation quite often go hand in hand, i.e. new processes are needed to produce new products. These processes may not necessarily lead to lower production costs (see Ebling et al., 2000). However, the simultaneity of product and process R&D is neglected in this paper to keep the empirical analysis tractable.

[2]In the following we use the subscript r to distinguish parameters related to process innovation from parameters related to product innovation. For the latter we use the subscript d.

absence of spillovers. If spillovers exist, the elasticity is equal to $\alpha_r + \gamma_r \frac{r_i}{\bar{r}_i}$. N is the equilibrium number of firms in the industry and A_c a scale or efficiency parameter.

Firms' demand conditions are affected by own as well as pooled industry product R&D. Own product R&D affects the firms' demand conditions through relative changes in utility which expand the demand for the firms' products and hence allow firms to achieve higher prices given the overall price level in the industry. Following Levin and Reiss (1988) the inverse demand function firm i is facing can be defined as

$$P_i \;=\; P(\bar{Q})G_i \;=\; A_p \bar{Q}^{-1/\epsilon} G_i. \tag{3}$$

G_i represents the perceived quality or attractiveness of firm i's product. $P(\cdot)$ is an industry price index depending on

$$\bar{Q} \;=\; \sum_{j=1}^{N} G_j q_j \tag{4}$$

as a weighted aggregate industry output index. Aggregate output depends on the unobservable individual firm's output q_j with the perceived quality of products as weights. ϵ is the constant price elasticity of industry demand.

The perceived product quality depends on own as well as pooled industry product R&D. Own and rival product R&D are considered as perfect substitutes in the industry pool. Analogously to the unit cost function the quality function is defined as a Cobb–Douglas function

$$G_i \;=\; G_i(d_i, \bar{d}_i) \;=\; A_g d_i^{\alpha_d} \bar{d}_i^{\gamma_d}. \tag{5}$$

d_i is product R&D done by the i-th firm and $\bar{d}_i$ is the analog to the knowledge pool of process R&D:

$$\bar{d}_i \;=\; d_i + \omega_d \sum_{j \neq i}^{N} d_i. \tag{6}$$

The scalar parameter ω_d represents the extent of product R&D spillovers. The parameter γ_d, the elasticity of perceived product quality with respect to the industry product R&D pool, can be seen as the productivity of spillovers. α_d is the elasticity of perceived quality in the absence of spillovers. If spillovers exist, the elasticity is $\alpha_d + \gamma_d \frac{d_i}{\bar{d}_i}$. A_g is a scale parameter.

Firms are maximizing their profits with respect to process and product R&D r_i, d_i and output q_i:

$$\max_{q_i,r_i,d_i} \Big(P_i(q_i, Q(q_i), d_i, \bar{d}_i(d_i)) - C_i(r_i, \bar{r}_i(r_i))\Big)q_i - r_i - d_i - k_i\,. \tag{7}$$

k_i are fixed costs of production. For simplicity a symmetric equilibrium is assumed, i.e. each firm confronts the same decision problem. Furthermore, the firms are assumed to have Cournot-Nash conjectures regarding output and R&D decisions of other firms. The three first-order conditions and the free-entry zero–profit condition characterize the equilibrium.

After aggregating across firms and some transformations Levin and Reiss (1988) derive the following two equations for industry process and product R&D:

$$\frac{R}{1-(R+D+K)} = \alpha_r + \frac{\gamma_r}{1+\omega_r(N-1)} \tag{8}$$

$$D = \alpha_d\left[1-\frac{H}{\epsilon}\right] + \gamma_d\left[\frac{1}{1+\omega_d(N-1)} - \frac{H}{\epsilon}\right]. \tag{9}$$

Equation (8) and (9) can be aggregated to one R&D equation

$$\begin{aligned}&\frac{R+D}{1-(R+D+K)} \\ &= \alpha_r + \alpha_d + \frac{\gamma_r}{1+\omega_r(N-1)} + \frac{\gamma_d}{1-\frac{H}{\epsilon}}\left(\frac{1}{1+\omega_d(N-1)} - \frac{H}{\epsilon}\right).\end{aligned} \tag{10}$$

The variables R and D are the ratios of industry process and product R&D to industry sales, respectively. K represents the ratio of other industry fixed costs to industry sales. The left-hand side of equation (10) can be interpreted as the ratio of industry R&D costs to total variable production costs of the industry. $H = \frac{1}{N}$ represents the Herfindahl index of concentration if all firms in an industry have equal market shares. Coefficients α_r and α_d cover the technological opportunities firms are facing when engaging in R&D. Terms containing γ_r, γ_d and ω_r, ω_d reflect to aspects of appropriability conditions: the extent and productivity of spillovers, respectively.

Levin and Reiss (1988) derive another equation from the optimization process (7) determining the endogenous market structure.

$$H = \epsilon\,(R+D+K) \tag{11}$$

in which market concentration is explained by demand conditions reflected by the price elasticity of demand ϵ, the costs of industry R&D-to-sales ratio $(R+D)$ and the ratio of industry fixed costs to industry sales (K).

3 The Empirical Specification

3.1 The Data Set

We use data from the Mannheim Innovation Panel (MIP) to test the empirical implications of the outlined model for Germany. The MIP is the official German innovation survey in the manufacturing sector conducted by ZEW in co–operation with infas Institute for Applied Social Science on behalf of the German government. It contains seven years of cross sections of business data covering the period between 1992 and 1998. The sample of the MIP is representative for the German manufacturing sector. Since expansion factors are available, we are able to expand the relevant variables on innovation and R&D activities for the German economy on the sector level.[3] See appendix A as well as Janz et al. (2001) and references cited therein for more detailed information on the MIP and the expansion techniques.

3.2 The R&D equation

Since information on R&D expenditure generally is not available for process and product R&D separately, we use equation (10) as R&D equation. In a functionalized version, the sector level R&D equation can be defined as

$$\begin{aligned}\frac{R_{st}+D_{st}}{1-(R_{st}+D_{st}+K_{st})} &= \alpha(A_{st}) + \frac{\gamma_r(\Gamma_{rst})}{1+\omega_r(\Omega_{rst})(N_{st}-1)} \\ &\quad + \frac{\gamma_d(\Gamma_{dst})}{1-\frac{H_{st}}{\epsilon_{st}}}\left(\frac{1}{1+\omega_d(\Omega_{dst})(N_{st}-1)} - \frac{H_{st}}{\epsilon_{st}}\right) \\ &\quad (s=1,\ldots,S; t=1,\ldots,T).\end{aligned} \tag{12}$$

The cross–sectional index s identifies sectors where the total number of sectors considered is S. We observe a time period, indicated by t, of T years. Note that equation (12) is non–linear in the parameters of interest.

[3]We use 2–digit NACE classes to define industry sectors.

The parameters reflecting technological opportunities and appropriability conditions, $\alpha = \alpha_r + \alpha_d$, γ_r, γ_d and ω_r, ω_d are functionalized by variables or vectors of variables A_{st}, $\Gamma_{rst}, \Gamma_{dst}$, $\Omega_{rst}, \Omega_{dst}$, respectively.

To account for inter–industry differences in technological opportunity we use three dummy variables for the most innovative sectors (see Ebling et al., 2000). These are the chemical industry, the manufacturing of transportation equipment industry (including manufacturing of motor vehicles) and the electrical goods industry. We do not distinguish between technological opportunities regarding product and process innovation since the share of both, product and process innovators, are well above average in these industries. We expect a positive sign of the referring parameters. Additionally, we assume differences in technological opportunity between East and West Germany and include the shares of firms located in East Germany. Only 7% of the whole German R&D expenditure can be attributed to firms in Eastern Germany (see Ebling et al., 2000). We expect a negative impact of the share of East German firms on R&D activity in the considered sector.

The productivity of spillovers γ_d, γ_d are part of the non–linear terms of equation (12). We functionalize them by variables pointing out the importance of external knowledge for the innovation activities of firms in these industries. Within the MIP, firms were asked if items in a given list of sources of information were important for their innovation activities. The expansion of the answers allows to calculate the share of firms in a sector which use given sources of information. We restrict our attention to external knowledge and differentiate between customers, suppliers, competitors and science as sources for knowledge. According to Czarnitzky et al. (2000), especially suppliers give important incentives to innovate production processes. Scientific institutes and universities may be interpreted as suppliers of knowledge as well. We use both, the share of firms using suppliers and science as information sources to functionalize the productivity of spillover concerning process innovations γ_r. The share of firms using customers or competitors as information sources are used to functionalize the productivity of spillover concerning product innovations, γ_d. Spillover effects could arise by imitating products from competitors or by co–operating with competitors or customers. We expect positive impacts of the usage of information sources on R&D expenditure.

The extent of knowledge spillover ω_d, ω_r defines the formation of the knowledge pool which may spill over and be more or less productive in decreasing cost or increasing markets. In a negative sense, they may be interpreted as the extent of innovation protection. We use the information on patent protection available in the MIP to functionalize the extent of knowledge spillover. Firms give information on patent applications in the last three years. To differentiate between product and process innovation, we weight the share of firms with patent applications by the information on the importance of patents for either product or process innovations from the first wave of the MIP in 1992. We get a measure of the relative amount of knowledge protected (and thus not spilling over) for product and process innovations, respectively. For that reason, we assume a negative impact on the extent of research activities.

3.3 The concentration equation

Following Levin and Reiss (1988), we take a generalized log–linear specification of the concentration equation. Additionally, we allow for a time lag in the effect of R&D on market concentration which enables us to distinguish between short and long run effects of R&D on concentration

$$\begin{aligned} \ln H_{st} &= \beta_0 + \beta_1 \ln \epsilon_{st} + \beta_2 \ln(R_{st} + D_{st} + K_{st}) \\ &\quad + \beta_3 \ln(R_{s,t-1} + D_{s,t-1} + K_{s,t-1}) \\ &\qquad\qquad (s = 1, \ldots, S; t = 1, \ldots, T). \end{aligned} \tag{13}$$

Equation (11) is nested in the long run if $\beta_0 = 0$, $\beta_1 = 1$ and $\beta_2 + \beta_3 = 1$.

The equation contains three theoretical constructs that are not directly observable: market concentration measured by the Herfindahl index H_{st}, fixed costs K_{st}, and the price elasticity of demand ϵ_{st}. We calculate the Herfindahl index from estimated market shares of firms in the Mannheim enterprise panel (MUP), which includes 12,000 firms.[4] The price elasticity of demand of each industry results from a discrete approximation with producer price indices and industry sales published by the German statistical office. Our proxy for fixed costs is depreciation as reported in line of business data by the same institution.

We allow a time lag in the effect of the R&D expenditure on sales concentration. Past and actual decisions of firms concerning the extent of R&D expenditure determine

[4]See Appendix A for more detailed information on the MUP.

the knowledge pool of an industry. To this extent we assume a partial adjustment process of market structure.

Table 1 presents descriptive statistics of the variables used in the estimation.

Table 1: Descriptive Statistics

Variables	Mean	Std.dev.	Min	Max
Herfindahl Index	0.23	0.21	0.04	0.94
R&D exp./Sales	0.025	0.030	0.001	0.174
R&D exp./Total Costs	0.033	0.039	0.001	0.210
Fixed Costs/Sales	0.058	0.052	0.011	0.264
Price Elasticity	-.99	-.05	-1.13	-.60
Extent of Spillover:				
Share of firms [%]				
Product Patents	12.6	9.5	0	35.9
Process Patents	10.1	10.1	0	45.3
Productivity of Spillover:				
Share of firms [%]				
Customers	59.7	19.4	5.7	98.3
Competitors	51.8	18.8	8.8	83.7
Suppliers	51.4	17.1	9.0	94.7
Science	18.8	11.5	0	56.8

4 The Estimation Method

Equations (12) and (13) describe a simultaneous dynamic equation system. We use Generalized Method of Moments (GMM) techniques for dynamic panel data to estimate the parameters of interest (Hansen, 1982, Gallant, 1987, Cornwell et al., 1992).

Following Gallant (1987), the system to be estimated can be defined as

$$f_g(y_{st}, x_{st}, \beta_g) = e_{gst} \quad (g = 1, 2;\ s = 1, \ldots, S;\ t = 0, \ldots, T) \tag{14}$$

where g is the number of the equations. t indexes observations over time and s indicates the cross-sectional unit. $f_g(\cdot, \cdot, \cdot)$ is a real valued function. The 2–dimensional vector of endogenous variables is characterized by y_{st}. The vector x_{st} summarizes all explanatory variables. It may additionally contain lagged values of the endogenous and the explanatory variables. Explanatory variables can be selected from x_{st} by a proper selection of functions f_g. As usual β_g is a vector of the unknown parameters to be estimated. The unobservable error term e_{gst} may in general be heteroscedastic and serially correlated.

For the estimation procedure we have to specify a vector of instrumental variables z_{st} orthogonal to the error term e_{gst} being a sub–vector of x_{st}

$$z_{st} = Z(x_{st}). \tag{15}$$

We use the orthogonality property of z_{st} to form theoretical moment conditions

$$m(\beta) = \mathrm{E}\left(m(y_{st}, x_{st}, \beta)\right) = 0 \tag{16}$$

with

$$m(y_{st}, x_{st}, \beta) = f(y_{st}, x_{st}, \beta) \otimes z_{st}.$$

The right direct matrix product, well known as the Kronecker product, is denoted by $\otimes$. $\beta = (\beta_1, \beta_2)'$ denotes the vector or parameters and $f(\cdot) = (f_1(\cdot), f_2(\cdot))'$ summarizes both equations.

The number of orthogonality restrictions generated through (16) in general is higher than the number of parameters to be estimated. In consequence, we cannot set to zero the empirical counterparts of (16) and use a criterion function quadratic in the empirical moments

$$m_{ST}(\beta) = \frac{1}{ST} \sum_{s=1}^{S} \sum_{t=1}^{T} m(y_{st}, x_{st}, \beta) \tag{17}$$

which has to be minimized with respect to the parameters to be estimated. The GMM–estimator of β is defined as that value $\hat{\beta}$ that minimizes the criterion function

$$S(\beta, V) \quad = \quad [STm_{ST}(\beta)]'V^{-1}[STm_{ST}(\beta)]. \tag{18}$$

The resulting GMM–estimator is consistent and asymptotically normal for any weighting matrix V which is non–stochastic and positive definite. The GMM–estimator is asymptotically efficient in the chosen specification for either $S \to \infty$ or $T \to \infty$ if a matrix proportional to the variance–covariance matrix of the empirical moments

$$V = Cov\left\{[STm_{ST}(\beta)]\,,[STm_{ST}(\beta)]'\right\} \tag{19}$$

is used as weighting matrix.[5]

We allow the error terms e_{gst} in equation (14) to be heteroscedastic across time and firms as well as serially correlated over time. In estimating the variance–covariance matrix (19) we allow for first order serial correlation obtaining a heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator. To ensure the positive definiteness of the covariance matrix of the orthogonality conditions the spectral density kernel is used as weights. We use the Parzen weights (Parzen, 1957) discussed by Gallant (1987) and Andrews (1991) instead of the usual Bartlett weights (Newey and West, 1987) since Andrews (1991) has shown that the Bartlett kernel is somewhat inferior in terms of asymptotic mean–squared error among the class of kernels that generate positive semi-definite estimated matrices.

As the number of moment conditions $m(\cdot)$ is higher than the dimension of β we are generating overidentifying restrictions equal to the number of orthogonality conditions which are not set to zero by the linear combination of orthogonality conditions defining the GMM–estimator. We can use these free empirical moments to test for the null–hypothesis that the remaining theoretical orthogonality restrictions are equal to zero. Sargan (1958) and Hansen (1982) have shown that under the null–hypothesis the function (18) evaluated at the estimate is χ^2 distributed with degrees of freedom equal to the difference between the dimension of $m(\cdot)$ and β.

[5]Numerical algorithms determine the minimum of the criterion function (18). Initial conditions for estimation are obtained with usual three-stage least squares estimates. The computations are done with the software package TSP.

We used a pooled panel data approach to obtain estimates for the parameters. To check the assumption of pooling, we use the test for the presence of industry–specific effects developed by Holtz-Eakin (1988). Under the assumption of industry–specific effects the system (14) changes to

$$f_g(y_{st}, x_{st}, \beta_g) = f_{gs} + e_{gst} \quad (g = 1, 2;\ s = 1, \ldots, S;\ t = 0, \ldots, T) \tag{20}$$

where f_{gs} denotes stochastic effects constant over time and possibly correlated with parts of the variables x_{st}. To obtain a consistent estimator for fixed T the effects have to be filtered by a suitable filter matrix. Usually the first difference filter introduced by Anderson and Hsiao (1981,1982) is used as filtering matrix generating a moving–average error term of order one: $e_{gst} - e_{gs,t-1}$. In consequence, not all instruments in z_{st} maybe valid, since some of them may be orthogonal to e_{gst} but not to $e_{gs,t-1}$. The procedure of Holtz–Eakin (1988) tests the null–hypothesis that orthogonality conditions valid only in the absence of firm–specific effects are equal to zero. The test statistic is equal to the difference of the criterion–function under the null and under the alternative when the same matrix is used as weighting matrix. The resulting test statistic is χ^2–distributed with degrees of freedom equal to the number of additional orthogonality restrictions.

For testing the model assumption that equation (11) is nested in the long run, i.e. $\beta_2 + \beta_3 = 1$. We follow Gallant (1987, p. 457f.) and calculate a Likelihood Ratio type statistic which is the difference between the criterion–function evaluated at the restricted (nested) and unrestricted estimates. One has to use the same weighting matrix calculated under the null hypothesis in both terms. The test statistic is χ^2–distributed with degrees of freedom equal to the number of restrictions.

5 The Empirical Results

The parameters of the R&D–equation (12) and the market concentration equation (13) are estimated using aggregated data from the Mannheim Innovation Panel (MIP). We restrict the constant term in the market concentration equation to be zero to nest the monopoly case in which the Herfindahl index equals 1. To allow for possible endogeneity of the explanatory variables only lagged values of the explanatory variables are included in the list of instruments with the exception of the price elasticity of demand. Following Levin and Reiss (1988), the price elasticity is assumed to be pre–determined, i.e. current values enter the list of instruments. We use the same list of instruments for both equations: price elasticity of demand, shares of patents for product and process innovations respectively, innovation expenditure over sales, number of employees in logs, exports over sales, variables for the productivity of spillover as explained, share of firms in Eastern Germany and dummy variables indicating chemical industry, motor manufacturing industry, electrical goods industry, machine construction and the sector for medicine, technology of measurement and control engineering added by a constant term.

Table 2 summarizes the estimation results. The third and fourth column contain t–statistics and p–values for the marginal level of significance. First we have to check the suitability of the estimation procedure. The discussed test statistics are contained in the bottom of table 2. The test for overidentifying restrictions (Sargan, 1958 and Hansen, 1982) does not reject the validity of the instruments, i.e. the instruments are orthogonal to the error term. This result is supplemented by the test for the absence of industry–specific effects supporting the pooling approach.

The estimated coefficients of the concentration equation confirm our hypothesis about the impact of past innovation activities on sales concentration. In contrast, current R&D expenditures and fixed costs are negatively correlated with sales concentration. However, the long-run effect of R&D and fixed costs on sales concentration is clearly positive. Therefore, investigation in R&D is concentrating market shares and hence market power on few firms, at least in the long–run. But, the long–run model is rejected by the Likelihood Ratio type test. The price elasticity of demand has no significant impact on sales concentration. This confirms the results of Levin and Reiss (1988) who neither find any price effects.

Table 2: Result of the GMM-Estimation

Variables	Coefficients	t-statistic	p-value
Concentration equation			
$\ln(R_s + D_s + K_s)$	-0.751	-4.855	0.000
$\ln(R_s + D_s + K_s)_{t-1}$	0.922	4.439	0.000
$\ln(\epsilon_s)$	0.465	0.490	0.624
R&D Equation			
Constant	0.032	3.511	0.000
Technological Opportunities:			
Chemical Industry	0.029	2.149	0.032
Extent of Spillover:			
Product Patents	0.001	1.954	0.051
Process Patents	-0.000	-0.313	0.754
Productivity of Spillover:			
Customers	-0.299	-2.491	0.013
Competitors	-0.268	-3.044	0.002
Suppliers	0.455	2.317	0.021
Science	0.183	2.772	0.006
Marginal effect of concentration on innovation	-0.011	-7.109	0.000
Number of observations	110		
Overidentification test	27.126		0.251
Pooling test	0.424		1.000
Parameter restriction test	74.126		0.000

The second part of the table shows the results for the estimated coefficients of the second equation of the model. Contrary to our assumptions, the variables representing the technological opportunities of an industry have no significant effect on the R&D intensity, with exception of the dummy for chemical industry. Therefore, we select a specification only including the dummy representing the chemical industry which remains significant at a 5–percent level. As we find no significant effect of the variable measuring the share of East German firms in an industry on R&D intensity we leave it out, too. Patent protection for process innovation as a measure of the extent of knowledge spillover has no significant effect on R&D expenditure either. However, the effect of patents protecting product innovation is slightly positive. Patents do affect the extent of knowledge spillover for product R&D, but not for process R&D.

The importance of information sources for innovative activities, i.e. the productivity of spillovers, cannot be denied. All coefficients are significant, even at a 1–percent level. Suppliers of enterprises, acting as an information source for innovation, cause a rise in R&D expenditure. This effect concerns mainly process innovations which quite often are supplier dominated. This becomes quite obvious when thinking of modern IT–technologies. The same holds for information from scientific institutions. In contrast to our expectation, information from customers and competitors have a negative impact on R&D expenditure. This might indicate an increase in efficiency of the innovations especially caused by a tight relationship between firms and customers. Czarnitzky et al. (2000) calculated a higher share of sales with new products for these firms.

On average, the marginal effect of the concentration variable, the Herfindahl index, on the extent of R&D is negative. This confirms our hypothesis of a stimulating effect of higher competition on innovation activities in an industry. Innovation will support the increase of market power of few firms, but market power will lead to inertia when competition is hampered.

6 Conclusion

In this paper we have analyzed the interdependence between innovative activities and market structure for German industries following the approach of Levin and Reiss

(1988). In contrast to Levin and Reiss (1988), we use a simultaneous estimation framework and allowed for a time–lag in the effect of R&D on market concentration. We find a positive long run effect of innovation activities on sales concentration. The innovation input variable we use supports the shift of market shares and hence sales concentration which leads to greater market power of few firms in an industry. On the other hand we conclude, that firms are forced to innovate in a more competitive environment to withstand competitive pressure. Hence competition is a fundamental incentive to innovate. Our result supports the early thesis of Scherer (1967). An industry will not remain in a fixed state when a lack of competition leads to inertia and thus increases the chances for entrants in the market which will strengthen competition and innovation.

Future work will concentrate on two fields of research: since we found dynamic effects of R&D on market concentration, the static framework of Levin and Reiss (1988) will be extended using a dynamic optimization framework with adjustment costs for R&D–activities. Additionally we will expand our analysis on different forms of innovation activities beside R&D focusing especially on forms of innovation activities which are closer to the market. Our results confirm those of Levin and Reiss (1988) that marketing activities could be an essential determinant of market shares and thus market structure. Moreover, an examination of relationships at the level of the firm may give additional insight in the functioning of markets (see e.g. Harhoff, 1997).

A Appendix

A.1 The Mannheim Innovation Panel

The Mannheim Innovation Panel (MIP) started in 1993 as a voluntary mail survey and is constructed as a panel with yearly waves. Up to 1999 it has been running seven times in co-operation with infas Institute for Applied Social Science. The MIP is strongly based on the recommendations on innovation surveys manifested in the Oslo-Manual of the OECD and Eurostat (OECD, 1997). It gives basic information on product and process innovations, innovation activities and components of innovation expenditure related to these activities. Innovation expenditure comprises all current expenditure (personnel, materials, services, etc.) as well as capital expenditure for innovation. It includes R&D expenditure[6].

Most of the quantitative variables are available for every firm in every year. In our estimation we need sales, total wage costs, material costs and R&D expenditure.

The population of the MIP covers legally independent German firms in the sectors mining and manufacturing with at least 5 employees. In our estimation we use the NACE classes[7] 10, 15, 17-36. The sample of the MIP is drawn as a stratified random sample. Firm size (8 size classes according to the number of employees), branch of industry (according to 2-digit NACE classes) and region (East and West Germany) are used as stratifying variables.

Expansion factors have been constructed for single cross-sections taking into account the stratification as mentioned above. We expand the values of R&D for the years 1993 to 1999 at the 2-digit NACE level.

A.2 The Mannheim Foundation Panel

The Mannheim Enterprise Panel (MUP) is composed by information on a sample of 12,000 German firms, which is provided by CREDITREFORM[8]. The sample is stratified according to branches and an employment classification[9]. The available information, which we use for our purpose, includes industry classification, number of employees, sales, data regarding insolvency proceedings and date of last enquiry. We use information about sales and industry classification to calculate the Herfindahl index of markets' sales concentration.

[6]The definition of R&D according to OECD (1997) used in official R&D statistics is explicitly nested in the definition of innovation.

[7]NACE (Nomenclature générale des activités économique dans le Communautés européennes) as published by Eurostat.

[8]CREDITREFORM is Germany's largest credit rating agency and has most comprehensive database of German firms at its disposal.

[9]See Almus et al. (2000) for more detailed information on the MUP.

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