

STRATEGIC AND TACTICAL DECISIONS, SUNK COSTS AND FIRM SIZE EFFECTS IN R&D

Robert W. Vossen

SOM theme B: Marketing and Networks

STRATEGIC AND TACTICAL DECISIONS, SUNK COSTS AND FIRM SIZE EFFECTS IN R&D¹

Robert W. Vossen

Abstract

This paper links the empirical and theoretical traditions in innovation research by directly estimating a theoretical model of R&D and firm size. A distinction is made between a model to explain participation in R&D, and a model to explain the rate of expenditure in case of participation. Large firms are more likely to participate in R&D because, relative to risks, expected returns are higher for larger firms. However, the smaller firms that do engage in R&D, generally do so at a higher level of intensity, and more efficiently, than larger firms. Also, there is some indication that a fixed and sunk entry cost plays a role in the decision whether or not to engage in R&D

¹ The author is indebted to Bart Nooteboom and Geert Ridder for their valuable comments and suggestions.

1. Introduction

For a long time, game-theoretic models of innovation have only emphasized market structure, either comparing perfect competition with monopoly or oligopolistic structures, or analyzing the innovative incentives for n identical firms, and these models were used for theoretical analysis only. Nooteboom (1991) extended some of the game theoretic models mentioned earlier, among other things by incorporating several possible effects of scale.

The first is that beside an effect of the intensity of R&D expenditure on expected development time, there is also an effect of the level of expenditure (quality of the innovation aimed at) on profits in case of success. Secondly, in the relation between level of expenditure and profits, an effect of firm size is allowed: small firms may be more or less efficient with respect to the profit/cost ratio of R&D. And finally, beside the flow cost of R&D, there is a fixed entry cost, regardless of firm size. In addition, a distinction is made between a model to explain participation in R&D, and a model to explain the rate of expenditure in case of participation.

This formulation now makes it possible to link the empirical tradition (focusing primarily on firm size in a theoretically more loose, ad hoc fashion) and the theoretical tradition (focusing on market structure) in neo-Schumpeterian research, by directly estimating the theoretical model. In this way, the model provides the theoretical basis for a more profound interpretation of empirical results. Considering the sensitivity of model outcomes to the specific assumptions made, it is important also from a theoretical perspective to develop models that are empirically testable, unless the aim is a comparative study of extreme cases of market conditions, or it can be shown that the results can only be strengthened or will at least still hold if certain restrictive conditions are relaxed. Moreover, the combination of theoretical and empirical lines of research can give new directions for empirical work (e.g. data collection) as well as model building (modelling assumptions).

In the following paragraph, the specification of the model is presented. Then in paragraph 3 the participation and spending decisions are first estimated as independent decisions and next I allow for interdependence by rewriting the model as a 'type 2' Tobit model (Amemiya, 1986). In the closing paragraph, the results are discussed.

Large firms are more innovative in the sense that they are more likely to participate in R&D because, relative to risks, expected returns are higher for larger firms. There is some indication that a fixed and sunk entry cost plays a role in the decision whether or not to engage in R&D, which would also have a negative effect on the participation of smaller firms. In the presence of a positive correlation between the disturbance terms of the participation and spending models, small firm R&D is

overestimated in OLS regressions on a restricted sample of firms performing R&D due to sample selection bias. On the other hand, in many other data bases the innovative activity of smaller firms is structurally underestimated because mainly formal R&D is considered, rather than the broad measure of R&D that I employ here. On balance, I find that in three out of four classes of industries, the smaller firms that do engage in R&D, do so at a higher level of intensity. That is, they spend more per unit of firm size. According to the underlying model, and under the assumption that there are diminishing returns to scale in the selection of a development project, the fact that R&D expenditure increases less than proportionately with firm size means that, in these industries, smaller firms are more profit/cost efficient. This conclusion is supported by more direct investigations of the relation between innovative outputs and inputs.

2. Model Specification

As the basis for an empirical study of the relation between R&D and firm size, I employ a “patent race” type model, first proposed by Nootboom (1991), extending on earlier models by Loury (1979), Lee & Wilde (1980) and Dasgupta & Stiglitz (1980, 1981). It includes several possible effects of scale, and makes an explicit distinction between R&D participation and spending. Nootboom (1991) has shown that the divergent and sometimes contradictory results from the empirical literature, can be the consequence of mixing the following three aspects.

First the question of participation: what percentage of firms, in each given size class, takes part in R&D? Second the question of expenditure: if a firm takes part, how much does it spend on R&D? And finally the question of effectiveness: what proportion do proceeds and expense bear to one another? He illustrates that even with a uniformly increasing participation rate, and R&D spending per unit of firm size decreasing uniformly with firm size, the expected R&D intensity (probability of participation times R&D spending per unit of firm size) can be uniformly increasing with firm size, uniformly decreasing, or first increasing and then decreasing, depending on the relation between R&D effectiveness and firm size.

The importance of separating R&D participation and spending was also noted by Baldwin and Scott (1987), where they, discussing a study by Bound, Cummins, Griliches, Hall and Jaffe (1984) who find that empirical results differ depending on the number of small firms in the sample, put the case that what is observed is that relatively few smaller firms conduct R&D, and not that the small firms engaging in R&D spend less per unit of firm size than larger firms.

2.1 Basic Model

The basic assumptions and model specification are as follows.

Development time:

It is assumed that the R&D process is stochastic, with a Poisson incidence of success, which means that development time t follows the exponential distribution specified in (1).

$$f(t) = \lambda e^{-\lambda t} \quad (1)$$

where $f(t)$ is the probability density over development time t .

R&D is assumed to be a race between n contestants in which the winner takes all. Hence the race stops at time T , i.e. the moment when any contestant has achieved success. On the assumption that the stochastic process of development (1) applies independently to all n participants, the cumulative distribution function over T is²:

$$F(T) = 1 - \prod_{j=1}^n (1 - F_j(T)) = 1 - \prod_{j=1}^n (1 - (1 - e^{-I_j T})) = 1 - \prod_{j=1}^n e^{-I_j T} \quad (2)$$

We can rewrite this as follows.

$$F(T) = 1 - e^{-LT} \quad ; \text{ where } L = \sum_{j=1}^n I_j \quad (3)$$

Hence the probability density function over T is:

$$f(T) = L e^{-LT} \quad (4)$$

² See for instance Mood, Graybill and Boes (1974), p. 184.

Cost:

The Poisson parameter λ is an increasing function of the intensity of R&D expenditure γ . That is, firms can reduce their expected development time ($1/\lambda$) by concentrating expenditure in time.

Beside the *intensity*, contestants have to decide upon the *level* of R&D spending. They can aim for a more expensive, higher quality innovation with higher profits (in case the race is won) by increasing the level of expenditure c . Contestants maximize expected net returns with respect to both level and intensity of expenditure. One can speed up development by raising intensity without affecting the level of profitability, and one can raise the level of profitability, by aiming for more sophisticated versions of the object of development, with corresponding higher levels of flow cost and associated higher levels of returns, without affecting the speed of development.

Finally, in addition to the flow cost (intensity \times level) of R&D, which lasts for as long as the race does, there is a fixed and sunk entry cost a , which is independent from firm size. It enters the calculation only in so far as it is sunk, reflecting an effect of scale in the form of a threshold cost. Net present value of total cost is represented in (5).

$$C = a + \int_0^T g c S e^{-it} dt = a + \frac{g c S}{i} (1 - e^{-iT}) \quad (5)$$

where	C	= net present value of total cost
	a	= fixed and sunk entry cost
	T	= time at which the development stops
	γ	= intensity factor determining λ , with $\gamma=1$ as a 'standard' intensity
	c	= flow cost per unit of firm size, during development
	S	= firm size
	I	= discount rate

It now follows from (4) and (5) that expected cost is³:

³ Note that this expression holds under the assumption that $f(T)$ is as specified in (4), meaning that the race stops as soon as the first contestant has achieved success.

$$E(C) = a + \frac{g c S}{i} \int_0^{\infty} (1 - e^{-iT}) L e^{-LT} dT = a + \frac{g c S}{L+i} \quad (6)$$

Rewards:

The profits per unit of firm size b , are represented in (7).

$$b = \mathbf{b}_0 S^{b_2} c^{b_1} \quad (7)$$

In this relation between the level of expenditure and profits, an effect of firm size is allowed: smaller firms may be more or less efficient with respect to the profit/cost ratio of R&D. That is, $\beta_2 > 0$ means that larger firms are more efficient, and $\beta_2 < 0$ means that smaller firms are more efficient.

If success is achieved by a contestant j at time T (with probability density $\lambda_j e^{-\lambda_j T}$), he receives a reward bS (and nil otherwise). In net present value this is $bS e^{-iT}$. But the contestant only receives this reward if no other contestant has achieved success before T , which has probability $e^{-(L-\lambda_j)T}$, given that he himself has completed development at T . It now follows that expected rewards are as in (8)⁴.

$$E(R) = bS \int_0^{\infty} e^{-iT} e^{-(L-\lambda_j)T} \lambda_j e^{-\lambda_j T} dT = \frac{\lambda_j bS}{L+i} \quad (8)$$

Expected Returns:

Hence expected net present value of returns for any contestant is (dropping the subscripts):

$$E = E(R) - E(C) = -a + \frac{\lambda b - g c}{L+i} S \quad (9)$$

Maximizing E with respect to c yields

⁴ Here we use the assumption that the winner takes all.

$$b = \frac{\mathbf{g} c}{\mathbf{l} \mathbf{b}_1} \quad (10)$$

From (7) and (10) it follows that:

$$\hat{c} = \left(\frac{\mathbf{l}}{\mathbf{g}} \mathbf{b}_1 \mathbf{b}_0 S^{b_2} \right)^{\frac{1}{1-b_1}} \quad (11)$$

So we can rewrite E as follows

$$E = -a + \frac{\frac{1}{\mathbf{b}_1} - 1}{L+i} \mathbf{k} S^{l+m} \quad (12)$$

$$\text{where } \mathbf{k} = \mathbf{g} \left(\frac{\mathbf{l}}{\mathbf{g}} \mathbf{b}_1 \mathbf{b}_0 \right)^{\frac{1}{1-b_1}} \text{ and } \mathbf{m} = \frac{\mathbf{b}_2}{1-b_1}$$

2.2 Participation and Spending

Apart from the inclusion of scale effects, another important feature that distinguishes the model at hand from its predecessors is that it separates the strategic decision whether or not to participate in the R&D race, and the tactical decision of how much to spend in case of participation. With respect to this tactical decision the firm is treated as one rational, maximizing decision-maker. It is assumed that a firm maximizes expected net present value of returns with respect to the decision variables intensity (concentration in time) and level (quality of the innovation aimed at) of expenditure, in case of participation in the R&D race. This maximization, taking into account the effect of the level of R&D expenditure on the rewards of innovation, and the effect of the intensity of R&D expenditure on the speed of the innovation process and by that on the probability of winning the race, now leads to the following model of (optimal) annual R&D expenditure, in case of participation in the R&D race. Per unit of time, firms spend $\gamma c S$ plus part of the fixed cost a . Substituting for the optimal c (equation (11)) we get:

$$K = a/\Theta + \kappa S^{1+\mu} \quad (13)$$

where $K =$ expenditure per unit of time
 $a =$ fixed and sunk entry cost
 $\Theta =$ time period over which the fixed entry cost a is spread⁵
 κ and μ are as specified in (12)

The strategic decision whether or not to participate is then modelled as a trade-off between expected returns, and the risk that the R&D effort will have no success. With respect to this strategic decision, firms are not treated as single, perfectly rational decision-makers. The taking of this decision is viewed as a stochastic group process, a clash of different views and preferences. This makes that not only the R&D process and the race with competitors is stochastic, but also the outcome of the decision itself. Participation is not certain if it is by some standard rational to do so. Instead, for each potential entrant there is a probability of entry, which is a function of expected returns and risk. The rationale behind these assumptions is, that the design of projects is typically a technical activity about which consensus can be reached, while the decision whether or not to implement projects, in view of expected returns, risks, and alternatives, is more a political process on the basis of different goals and perspectives. As in the financial literature, for a higher level of risk firms will require a higher level of expected returns if they are to decide to engage in the development project under consideration. This approach connects with the dominant paradigms of the strategic decision making literature in several ways. Decision-makers can be incorrect in their assessment of expected returns and risk. So these decision-makers are boundedly rational, but not irrational: the probability of engaging in R&D increases with expected returns, and decreases with risk. Also, the decision whether or not to participate in R&D is viewed as the outcome of a group process, involving different stakeholders with possibly conflicting interests, views and preferences (political model of decision making). According to Eisenhardt and Zbaracki (1992) the debate over whether firms have single or multiple goals is no longer very controversial. Most management scholars accept the central ideas of the political perspective followed here that organizations are comprised of people with partially conflicting preferences, and that strategic decision making is ultimately political. Thirdly, modelling the outcome of the decision whether or not to engage in R&D as a stochastic process accounts for the influence of chance (cf. the garbage can perspective). Moreover, the approach followed here is in conformity with observed

⁵ Implicitly assuming straight-line depreciation. Depreciation is a noncash expense; it is important only because it reduces taxable income. Hence the actual depreciation method for tax purposes is not relevant here.

business practice. Decision making on the operational level generally has a deductive and analytical orientation, whereas on the strategic level it has a more inductive and intuitive orientation.

Hence the assumption is that the decision-makers proceed as follows. First one considers what optimal expected returns E would be in case of participation. This yields a corresponding level of risk r , defined as the probability of negative returns. The resulting values of E and r are then considered in the evaluation process represented by:

$$P = \frac{E}{E + \rho r} \quad (14)$$

where P = probability of participation
 E = (optimal) expected net present value of returns
 ρ = risk aversion parameter
 r = risk

In this specification, if expected returns are positive, they are considered, in principle, to be worthwhile, and if risk is zero and expected returns are positive, then entry is certain⁶.

Modelling the decision process stochastically in this way implies that if for a certain firm there is a project with the optimal combination of expected returns and risk, it is not certain that this project will be undertaken. It is only more likely than a project with less favourable values of E and r . Moreover, two or more projects, one being more favourable than the other, may be undertaken simultaneously. Next to viewing the strategic decision making as a political process, Nooteboom (1991) gives two additional ways in which this can be justified. First, undertaking several projects simultaneously may be both rational and realistic, as a way of spreading risk. Second, organizations may not know all strategic alternatives well enough, or be able to evaluate them jointly. So instead of simply selecting the best alternative, they may evaluate the options one by one.

Risk (r) is defined as the probability of negative net present value of returns. Even if a contestant wins the race, net returns will still be negative if development time T exceeds some critical value T^* . Winning at T yields a reward of bS , or bSe^{-it} in present value, and total cost is given in (5). Hence net present value of returns R for the contestant that wins at T is given by (15) below.

⁶ Note that the opportunity cost of capital is already incorporated in the discount rate used to calculate the net present value of returns E .

$$R = b S e^{-iT} - a - \frac{g c S}{i} (1 - e^{-iT}) \quad (15)$$

Substituting for the optimal project (see (10)), we have:

$$R = -a - \frac{g c S}{i} + \left(\frac{1}{i} + \frac{1}{\mathbf{l} \mathbf{b}_1} \right) g c S^{-iT} \quad (16)$$

From (16) it follows that $R \geq 0$ if:

$$T \leq T^* = -\frac{1}{i} \log \left\{ \left(1 + \frac{i a}{g c S} \right) \frac{\mathbf{l} \mathbf{b}_1}{\mathbf{l} \mathbf{b}_1 + i} \right\} \quad (17)$$

Now, given that the race is won, the probability that net present value of returns R is non-negative, according to (1), is given in (18).

$$P(T \leq T^* / \text{win}) = \int_0^{T^*} \mathbf{l} e^{-1t} dt = 1 - e^{-1T^*} \quad (18)$$

The unconditional probability of non-negative net returns is the probability that the development time $T \leq T^*$, multiplied by the probability that all other competitors have not yet completed their projects at that time, i.e. it is the probability of winning the race before T^* . Hence risk r , defined as the probability that the R&D effort will have no success is $P(R < 0) = 1 - P(R \geq 0)$.

$$r = 1 - \int_0^{T^*} \mathbf{l} e^{-1T} e^{-(L-1)T} dT = 1 - \frac{\mathbf{l}}{L} (1 - e^{-LT^*}) \quad (19)$$

Substituting for T^* (see (17)), r is as follows.

$$r = 1 - \frac{\mathbf{l}}{L} + \frac{\mathbf{l}}{L} \left\{ \left(1 + \frac{i a}{g c S} \right) \frac{\mathbf{l} \mathbf{b}_1}{\mathbf{l} \mathbf{b}_1 + i} \right\}^{\frac{L}{i}} \quad (20)$$

It follows from (20) that $dr/dS \leq 0$ if $a \geq 0$, meaning that risk decreases with firm size if the fixed entry cost are positive, and constant with firm size if there are no fixed entry cost.

3. Empirical Study

3.1 Empirical Specification

Equation (13) is the basic model of (optimal) annual R&D expenditure. Remember that, as mentioned earlier, $\beta_2 < 0$ (> 0) indicates that small firms (large firms) are more profit/cost efficient, and $\beta_1 < 1$ (> 1) indicates decreasing (increasing) returns to scale from the level of expenditure on the profitability of the innovation. This means that if there are decreasing returns to scale in the selection of the optimal development project ($\beta_1 < 1$), and we find empirically that $\mu < 0$, this would indicate that small firms are more efficient ($\beta_2 < 0$), since μ is defined as $\mu = \beta_2 / (1 - \beta_1)$. It seems reasonable to assume that $\beta_1 < 1$ on the basis of the general intuition that the market value of additional 'units of quality' will decrease relative to the cost, on the analogy of the law of diminishing marginal utility. If there were increasing returns to scale, it would be optimal for firms to increase their level of R&D expenditure indefinitely.

As the data I employ (see the next paragraph) include only R&D input measured as annual labour input, they do not include the amortized fixed entry cost a . Thus, the parameter a drops from the model. The expenditure model can now be linearized by performing a log-transformation⁷:

$$\log K = \log \kappa + (1 + \mu) \log S \quad (21)$$

The general specification of the participation model that I employ here was given in equation (14). Here, P is the probability of participation. In the optimum, expected net present value of returns $E = -a + h S^{1+\mu}$ (see equation (12))⁸, and ρ is a risk-aversion parameter. Risk r is a

⁷ This is justified, because K is heteroscedastic, with a variance depending on S , indicating that a multiplicative error term of the form $K = \kappa S^{1+\mu} \cdot e^v$ is appropriate.

⁸ Note that here, $h = \frac{\frac{1}{b_1} - 1}{L + i} g \left(\frac{1}{g} b_1 b_0 \right)^{\frac{1}{1-b_1}}$

complicated (decreasing) function of firm size S . Equation (20) implies $dr/dS < 0$ if $a > 0$, which is understandable: higher entry cost increases risk more for the smaller firm. The model for participation as a function of firm size now looks like this.

$$P = \frac{-a + hS^{1+m}}{-a + hS^{1+m} + \rho r(S)} \quad (22)$$

The function $r(S)$ has more parameters than could be estimated from the available data, so I tried to approximate the term ρr by different linear and non-linear functions of firm size S . A constant function turned out to be the best approximation (no significant firm size effect was found in any case). This is already an interesting result in itself because it would indicate that if risk (r) decreases with firm size, then apparently risk aversion (ρ) increases with firm size so that on balance $\rho(S) r(S)$ is approximately constant. Another possibility is of course that there is no firm size effect on either risk or risk aversion. However, it seems very plausible to assume that the risk of failure is lower for larger firms, since they have the means to undertake several projects simultaneously and thus spread their risks⁹. On the other hand, older firms in general are more conservative, or more risk averse, than younger firms. Felder, Licht, Nerlinger and Stahl (1996) find for instance, that older firms are less likely to perform R&D than younger firms of similar size in the German manufacturing industry. Since age is correlated strongly with size, older firms are generally larger than younger firms, this explains why risk aversion increases with firm size and is not, as in Nooteboom's original model specification, a constant.

Now, in order for the model to be identified we divide both numerator and denominator by h . The participation model to be estimated is now given in equation (23) below.

$$P = \frac{-a^* + S^{1+m}}{-a^* + S^{1+m} + \Xi} \quad (23)$$

where $a^* = a/h$
and $\Xi = \rho r/h$

⁹ and thereby lower their overall risk, as we know from the financial literature. For instance, for a portfolio of stock, the unique (unsystematic) risk of individual securities can potentially be 'diversified away'. What remains is the market risk or systematic risk.

3.2 Data

For this study I use three data sets. The first contains data from a national innovation survey conducted in the Netherlands in 1989 (with data on 1988), funded by the Netherlands' ministry of economic affairs) (Kleinknecht, Reijnen and Verweij, 1990). I used data on 2087 firms in the Dutch manufacturing industry, 1292 (62%) of which conducted some form of R&D in 1988.

The other two data sets are part of the Community Innovation Survey (CIS) project of the European Community (DG13), making use of a harmonized EU/OESO questionnaire for innovation surveys. I have made use of the Dutch and German surveys, with data on 1992. The Dutch survey was once again conducted by the University of Amsterdam Foundation for Economic Research (SEO) (Brouwer and Kleinknecht, 1994) and the German survey was conducted by the Centre for European Economic Research (ZEW) (Felder, Harhoff, Licht, Nerlinger and Stahl, 1994a; 1994b). For the Dutch database there were 1844 observations available, 651 (35%) of which reported some form of R&D in 1992. This is quite a dramatic falling off in the percentage of firms conducting R&D compared to 1988, when 62% of firms in our sample performed R&D. The decline is especially large for smaller firms, with often incidental and small scaled R&D. However, for firms conducting R&D, the average R&D intensity (R&D expenditure per unit of firm size) shows only a moderate decrease of 10% (Brouwer and Kleinknecht, 1994). Apparently, the period of decline in the Dutch business cycle has mainly influenced participation in R&D. For the German data, we have 2093 observations, with 1246 (60%) performing R&D. The economic circumstances in Germany were more favorable than in the Netherlands in 1992, due to the reunification of East and West-Germany several years earlier.

Data were available for individual respondents on SIC-code, firm size and R&D; both of the latter measured in terms of employment (full-time equivalents). Although there may be a bias here in the sense that small firm R&D is likely to be less capital intensive than large firm R&D, this bias will be largely compensated because firm size is measured in terms of employment as well. Any remaining bias probably affects the intensity parameter κ , rather than the more interesting firm size parameter μ .

A distinctive feature of these surveys, compared with common conventional R&D measurement, is that it measures not only formal R&D, but also small scale, informal R&D, accounting for the observation that the innovative activity of smaller firms is structurally underestimated if mainly formal R&D is considered (Archibugi, Cesaratto and Sirilli, 1991; Kleinknecht and Reijnen, 1991).

To allow for inter-industry differences in the parameters I used a classification introduced by Pavitt (1984), specifically based on the characteristics of innovations and of innovating firms, rather than on products and technology of production, as is the case with standard industrial classifications. Pavitt describes and explains sectoral diversity in innovative behaviour by identifying four categories of industries with differing technological trajectories, i.e. cost cutting, product design or mixed. He uses data collected by Townsend, Henwood, Thomas, Pavitt and Wyatt (1981), on the characteristics of about 2000 significant innovations in Britain between 1945 and 1979. The different technological trajectories are in turn explained by sectoral differences in the sources of technology, type of user, and means of appropriation, and some other characteristics of these trajectories are described. The four categories of firms in Pavitt's taxonomy are Supplier Dominated, Scale Intensive, Specialized Suppliers, and Science Based firms.

3.3 Independent Estimation

Simultaneous estimation of the expenditure model (21) and the participation model (23) requires maximization of the following Log-Likelihood.

$$\log L = \sum_{i=1}^{N_0} \log(1 - P_i) + \sum_{i=1}^{N_1} \log P_i - \frac{N_1}{2} \log \mathbf{s}^2 - \frac{1}{2} \mathbf{s}^2 \sum_{i=1}^{N_1} (\log K_i - \log \mathbf{k} - b \log S_i)^2 \quad (24)$$

where N_0 = the number of nonparticipants
and N_1 = the number of participants

Here, the common parameter μ is set equal in both models¹⁰, and industry dummies were placed on all parameters. The results of the simultaneous Maximum Likelihood estimation (24) for the Dutch 1988 data are given in table 1 below.

¹⁰ A likelihood ratio test was performed to check whether this is justified.

Table 1: Simultaneous Estimation (NL 1988)¹¹

{PRIVATE }Category of Firm	a* (st.d.)	log κ (st.d.)	μ (st.d.)	Ξ (st.d.)
Supplier Dominated	4.78*** (.973)	-3.34*** (.411)	-.311*** (.082)	14.8** (6.87)
Scale Intensive	3.86*** (1.08)	-3.73*** (.257)	-.194*** (.044)	18.3*** (4.28)
Specialized Suppliers	4.82*** (1.09)	-2.94*** (.362)	-.222*** (.074)	7.73*** (2.94)
Science Based	-.601 (13.5)	-3.86*** (.413)	-.008 (.075)	19.2** (10.3)
* : significant at the 10% level ** : significant at the 5% level *** : significant at the 1% level				

First we see that the effect of fixed entry cost a^* is significantly positive in the Supplier Dominated, Scale Intensive and Specialized Suppliers industries. For the Science-based industry it is not significantly different from zero. Beforehand one would expect fixed entry cost to be higher in the larger scaled industries (Scale Intensive and Science Based) and lower in the smaller scaled industries (Supplier Dominated and Specialized Suppliers). This is not what I find here. In fact the estimates of a^* show exactly the opposite pattern. One explanation is that I do not estimate the fixed entry cost a itself here, but a divided by a term h , which may also differ among industries. Among other things, the profitability of success in R&D β_0 (see model specification) is reflected in h , so it is possible that in a certain industry both the fixed entry cost a and the profitability of success are higher while a^* is lower, if the higher profitability outweighs the higher entry cost. Another explanation is that, since the fixed entry cost a enters the calculation only in as far as it is sunk, the entry cost may in fact be larger for the larger scaled industries, while only the sunk part of it is smaller. In any case I cannot make any strong statements about the magnitude of this entry cost in the different industries or about the statistical significance of a , since I do not estimate it directly. However, since, at least mathematically, $a^* = 0 \Leftrightarrow a = 0$, the results do suggest that a fixed and sunk entry cost plays a role.

Secondly we see that Ξ is significantly positive in all four categories. The estimates are of approximately the same order in the Supplier Dominated, Scale Intensive and Science-

¹¹ Standard deviations based on heteroscedasticity-consistent covariance matrix

based industries, but it is much lower for the Specialized Suppliers industry. A possible explanation for this is that in this particular industry, firms more frequently do R&D in direct cooperation with a client ('co-makership'), for instance in the Scale Intensive industry, so that overall the direct competition with respect to R&D is less intense than in other industries, which in turn means that the risk of another firm 'winning the race' is lower. Moreover, the presence of a customer, with a fit of the innovation to its needs, also reduces the market risk, i.e. the uncertainty with respect to whether or not there will be a (large enough) market for the innovation.

For all Pavitt sectors except Science Based industry R&D, expenditure of firms conducting R&D increases less than proportionately with firm size ($\mu < 0$). According to the underlying model, and under the assumption that there are decreasing returns to scale in the relation between level of R&D expenditure and profits in case of success ($\beta_1 < 1$, see model specification), the implication is that smaller firms are more R&D efficient. As expected, the effect is strongest in Supplier Dominated and Specialized Suppliers industries. Contrary to expectation, the effect is also found for Scale Intensive industry. The effect is strongest for the Supplier Dominated category, followed by Specialized Suppliers and Scale Intensive industries, respectively. For Science Based industry I find no significant difference between small and large firms. The results from estimating the model with the Dutch data on 1992 are given in table 2.

Table 2: Simultaneous Estimation (NL 1992)¹²

{PRIVATE }Category of Firm	a* (st.d.)	log κ (st.d.)	μ (st.d.)	Ξ (st.d.)
Supplier Dominated	3.86** (1.78)	-3.45*** (.714)	-.308** (.135)	73.5* (55.2)
Scale Intensive	4.99*** (1.61)	-3.93*** (.410)	-.202*** (.061)	51.4*** (18.2)
Specialized Suppliers	-1.51 (9.98)	-3.97*** (.606)	-.085 (.109)	55.9* (34.9)
Science Based	-20.7 (37.6)	-3.74*** (.552)	-.070 (.087)	100* (74.1)
* : significant at the 10% level ** : significant at the 5% level *** : significant at the 1% level				

¹² Standard deviations based on heteroscedasticity-consistent covariance matrix

Comparing these estimates with those from the 1988 data (see table 1), we first of all see a sharp increase in the estimates of Ξ . Apparently, in economically more trying times, firms either consider the risk of performing R&D to be higher, or are less willing to take risks (have higher risk aversion), or both. Since in the participation decision, the relative weight of the term Ξ is higher for smaller firms, which have lower expected returns, this explains why the percentage of firms performing R&D, and especially of smaller firms, is lower in 1992, compared to 1988. Also we see that the estimate of Ξ is no longer lowest for the Specialized Suppliers industry. However, the parameters a^* and Ξ are negatively correlated, meaning that if for this industry we would fix a^* to zero¹³, this would lower the estimate of Ξ . Hence what we find here is not really in flat contradiction with the earlier finding. There I hypothesized that the lower value of Ξ for the Specialized Suppliers industry is caused by more frequent R&D in direct cooperation with a client ('co-makership'), for instance in the Scale Intensive industry, so that overall the direct competition with respect to R&D is less intense than in other industries, which in turn means that the risk of another firm 'winning the race' is lower. With the new 1992 database the opportunity presents itself to check whether or not this is in fact the case. Of the 1844 firms in the sample, 1161 answered the question on R&D cooperation. The percentage of firms reporting to be engaged in some form of R&D cooperation was not significantly different between the Specialized Suppliers industry (32 %) and the other three industries (31%). Of the cooperating firms however, the percentage of firms cooperating with clients was highest in the Specialized Suppliers industry with 57% against 49% in the other industries, or 18% against 15% in total (i.e. of all firms in the sample, cooperating or not). This offers some direct support for the above-mentioned hypothesis.

The estimate of the firm size parameter μ has also increased for the Specialized Suppliers industry, so that it is no longer significantly negative. For the other three industries, it remains virtually unchanged. Also, again for the Specialized Suppliers industry, a^* has decreased to a point where it is no longer significantly different from zero. For the Supplier Dominated and Scale Intensive industries, a^* is still significantly positive, while for the Science Based industry, as before, it is still not significantly different from zero.

For the German data, the estimation results are given in table 3.

¹³ Note that a^* is negative, but not significantly different from zero.

Table 3: Simultaneous Estimation (D 1992)¹⁴

{PRIVATE }Category of Firm	a^* (st.d.)	$\log \kappa$ (st.d.)	μ (st.d.)	Ξ (st.d.)
Supplier Dominated	-.181 (3.20)	-2.13 ^{***} (.378)	-.398 ^{***} (.068)	29.3 ^{**} (14.5)
Scale Intensive	1.30 (2.22)	-2.46 ^{***} (.282)	-.296 ^{***} (.042)	26.0 ^{***} (8.00)
Specialized Suppliers	.508 (2.00)	-2.27 ^{***} (.249)	-.235 ^{***} (.032)	15.8 ^{***} (3.49)
Science Based	-53.7 (58.2)	-2.62 ^{***} (.307)	-.142 ^{***} (.043)	54.2 [*] (35.0)
<p>* : significant at the 10% level ** : significant at the 5% level *** : significant at the 1% level</p>				

First we see that the firm size parameter μ is lower than in the Dutch case. For these German data μ is significantly negative in all four industries, even for the Science Based industry. Also, we see that here Ξ is again clearly lowest for the Specialized Suppliers industry, reconfirming the result I found in the Dutch industry for 1988. The estimates of a^* are not significantly different from zero in any industry here, possibly because in the former East Germany large R&D and investment subsidies are granted, lowering the fixed and sunk entry cost associated with performing R&D.

3.4 Allowing for Interdependence of Disturbances

Crepon, Duguet and Kabla (1996) state that estimates of a model of R&D spending based on OLS regressions are biased because the dependent variable (R&D spending) is limited. There are no data on innovative inputs for firms that have decided not to engage in R&D. The simple Tobit model is also inadequate because there is a decision process generating the data on participation or non-participation, so that we do not observe a mere truncation. This is true only if the participation decision and the spending decision are not independent. To check whether or not there is independence in a statistical sense between the participation model and the

¹⁴ Standard deviations based on heteroscedasticity-consistent covariance matrix

spending model, we need to rewrite these models as follows. As a stochastic specification that is equivalent to the original model, I rewrite equations (21) and (23) as a 'type 2' Tobit model (Amemiya, 1986), so that we can allow for correlation between the disturbance terms. We get the following.

$$\log K_i = \log \kappa + (1+\mu) \log S_i + u_i \quad (25)$$

with $u_i \sim N(0, \sigma^2)$

$$y_i^* = \log(S_i^{1+m} - a^*) - \log \Xi - e_i \quad ; \text{ with } F(e_i) = \frac{e^{e_i}}{1 + e^{e_i}} \quad (26)$$

We observe $y_i = \begin{cases} 1 & \text{if } y_i^* > 0 & (\text{participation}) \\ 0 & \text{if } y_i^* \leq 0 & (\text{non-participation}) \end{cases}$ and $\log K_i$ is only observed if $y_i = 1$.

As ε is specified to have the (logistic) distribution function $F(\varepsilon)$, the transformed variable $\varepsilon^* = \Phi^{-1}(F(\varepsilon))$ will be a random variable with distribution function $\Phi(\varepsilon^*)$ (Lee, 1982), i.e. $\varepsilon^* \sim N(0,1)$. Now, since $y_i = 1 \Leftrightarrow \log(S_i^{1+\mu} - a^*) - \log \Xi > \varepsilon_i \Leftrightarrow \Phi^{-1}F[\log(S_i^{1+\mu} - a^*) - \log \Xi] > \varepsilon_i^*$, we can rewrite the latent regression (26) as follows.

$$y_i^{**} = \Phi^{-1}F[\log(S_i^{1+\mu} - a^*) - \log \Xi] - \varepsilon_i^* \quad ; \text{ with } \varepsilon_i^* \sim N(0,1) \quad (27)$$

So, for simultaneous estimation of equations (25) and (27), with

$(u, \mathbf{e}^*) \sim N_2 \left(0, \begin{pmatrix} \mathbf{s}^2 & \mathbf{r s} \\ \mathbf{r s} & 1 \end{pmatrix} \right)$, the likelihood function to be maximized is¹⁵:

$$L = \prod_{y_i=0} [1 - \Phi(\Phi^{-1}F[\log(S_i^{1+m} - a^*) - \log \Xi])] \times \prod_{y_i=1} \Phi \{ [\Phi^{-1}F[\log(S_i^{1+m} - a^*) - \log \Xi] + \mathbf{r s}^{-1}(\log K_i - \log \mathbf{k} - (1+m)\log S_i)] \times [1 - \mathbf{r}^2]^{1/2} \} \cdot \mathbf{s}^{-1} \mathbf{f}[\mathbf{s}^{-1}(\log K_i - \log \mathbf{k} - (1+m)\log S_i)] \quad (28)$$

¹⁵ Note that this likelihood reduces to the simple, 'independent' likelihood given in equation (24) if there is no interdependence, i.e. $\rho = 0$.

The first part of this likelihood reduces to $\prod_{y_i=0} (1 - F[\log(S_i^{l+m} - a) - \log r])$. For the second part however, I had to use the following rational approximation for $\Phi^{-1}(p)$ (Zelen and Severo, 1965). For $0 < p \leq .5$ we have¹⁶

$$\Phi^{-1}(p) \approx t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} ; \text{ with } t = \sqrt{\log \frac{1}{p^2}} \quad (29)$$

where $c_0 = 2.515517$ $d_1 = 1.432788$
 $c_1 = 0.802853$ $d_2 = 0.189269$
 $c_2 = 0.010328$ $d_3 = 0.001308$

I estimated this model for all three databases that I employed earlier. The results are given in tables 4 to 6.

Table 4: Tobit model with NL-1988 data¹⁷

{PRIVATE }Category of Firm	a* (st.d.)	log κ (st.d.)	μ (st.d.)	Ξ (st.d.)	ρ (st.d.)
Supplier Dominated	4.86** (2.14)	-4.26*** (.463)	-.181** (.090)	30.4** (15.1)	.389*** (.071)
Scale Intensive	3.98*** (1.65)	-4.44*** (.293)	-.095** (.049)	29.7*** (7.61)	
Specialized Suppliers	5.90*** (1.48)	-3.55*** (.395)	-.126* (.079)	12.1*** (4.80)	
Science Based	.085 (14.1)	-4.30*** (.424)	.055 (.076)	24.7** (12.4)	
* : significant at the 10% level ** : significant at the 5% level *** : significant at the 1% level					

¹⁶ For $.5 < p < 1$ we have $\Phi^{-1}(p) = -\Phi^{-1}(1-p)$.

¹⁷ Standard deviations based on heteroscedasticity-consistent covariance matrix

Table 5: Tobit model with NL-1992 data¹⁸

{PRIVATE }Category of Firm	a* (st.d.)	log κ (st.d.)	μ (st.d.)	Ξ (st.d.)	ρ (st.d.)
Supplier Dominated	3.88** (2.37)	-3.97*** (.779)	-.257** (.134)	97.3* (72.7)	.199 (.202)
Scale Intensive	4.94** (2.32)	-4.43*** (.683)	-.139* (.093)	72.1** (36.3)	
Specialized Suppliers	-4.05 (13.3)	-4.38*** (.730)	-.031 (.121)	73.5* (48.0)	
Science Based	-29.7 (46.1)	-4.13*** (.672)	-.023 (.094)	131* (92.9)	
<p>* : significant at the 10% level ** : significant at the 5% level *** : significant at the 1% level</p>					

Table 6: Tobit model with D-1992 data¹⁹

{PRIVATE }Category of Firm	a* (st.d.)	log κ (st.d.)	μ (st.d.)	Ξ (st.d.)	ρ (st.d.)
Supplier Dominated	-13.1 (10.2)	-4.23*** (.448)	-.172** (.082)	116** (52.2)	.927*** (.012)
Scale Intensive	-2.34 (3.81)	-4.22*** (.273)	-.088** (.042)	75.9*** (18.9)	
Specialized Suppliers	.494 (2.34)	-3.62*** (.243)	-.051* (.035)	36.1*** (7.74)	
Science Based	-13.0 (14.7)	-3.44*** (.317)	-.050 (.049)	39.2*** (15.2)	
<p>* : significant at the 10% level ** : significant at the 5% level *** : significant at the 1% level</p>					

¹⁸ Standard deviations based on heteroscedasticity-consistent covariance matrix

¹⁹ Standard deviations based on heteroscedasticity-consistent covariance matrix

From these tables we see a significant correlation coefficient (ρ) between the disturbance terms of the participation and spending models in two out of three cases. Comparing the estimates of the other parameters to those obtained from the independent estimation, we first see an increase in the estimates of the firm size parameter μ . For the NL 1988 data, the correlation coefficient of .4 leads to an average increase in μ of .1. The (non-significant) correlation coefficient of .2 for the NL 1992 data raises μ by .05 on average, and the high correlation coefficient (.9) for the German data yields an average increase in the estimates of μ of .18. However, the change in magnitude of these parameter estimates is not so large as to change the main results from the independent estimations. For the NL 1988 data, μ is still significantly negative (at least at the 10% level) for the Supplier Dominated, Scale Intensive, and Specialized Suppliers industries, and not significantly different from zero for the Science Based industry. Also, for the NL 1992 data, as before it is significantly negative for the Supplier Dominated and Scale Intensive, and not significantly different from zero for the Specialized Suppliers and Science Based industries. For the German case, μ is now no longer significantly different from zero for the Science Based industry, as was consistently found for the other two datasets. In the other three industries, it is still significantly negative.

Secondly, we see an increase in the estimates of Ξ , which is also higher for higher values of the correlation coefficient ρ ²⁰. Ξ remains significantly positive in all industries. The estimates of a^* are not significantly affected, they are significantly positive in the Supplier Dominated and Scale Intensive industries for the NL 1988 and 1992 data, in the Specialized Suppliers industry for the NL 1988 data, and not significantly different from zero in all other cases, as before.

4. Conclusion

The inclusion of effects of firm size in the model I employed here made it possible to link the empirical and theoretical traditions in neo-Schumpeterian research by directly estimating a theoretical model of R&D and firm size. In the specification of the model, a hybrid approach was taken. With respect to the tactical and more technical decision of how much to spend in case of participation, firms are treated as a single rational decision maker, whereas the more strategic and political decision whether or not to participate is viewed as a stochastic group

²⁰ Only for the D 1992 data, Ξ has decreased for the Science Based industry. This is probably caused by the negative correlation between Ξ and a^* , which has increased by 40 (but is still not significantly different from zero).

process, thus connecting with the dominant paradigms in the modern strategic decision making literature.

The empirical results show that small firms systematically participate less in R&D than large firms do. Large firms are thus more innovative in the sense that they are more likely to participate in R&D because, relative to risks, expected returns are higher for larger firms. This gives an alternative explanation to the question raised by Cohen and Klepper (1996) when they ask themselves if large firm R&D is less productive than small firm R&D, why are large firms more likely to conduct R&D and why do they conduct more R&D? I find the product of risk aversion and risk to be significantly positive in all cases, and constant with firm size. Assuming that risk in fact is lower for larger firms (by diversifying it over several simultaneously carried out R&D projects, and because the presence of a fixed entry cost yields a higher risk for smaller firms), the implication is that smaller (younger) firms are less risk averse than larger (older) firms. An interesting industry effect is that the risk factor is lower for the Specialized Suppliers industry than for the other industries because in this industry, firms more frequently do R&D in direct cooperation with a client ('co-makship'), for instance in the Scale Intensive industry, so that overall the direct competition with respect to R&D is less intense than in other industries, which in turn means that the risk of another firm 'winning the race' is lower. The sharp increase in the estimates of Ξ (risk aversion times risk) between 1988 and 1992 explains the dramatic falling off in the percentage (from 62% to 35%) of firms conducting R&D in the Netherlands in this period. The average R&D intensity (R&D expenditure per unit of firm size) of firms performing R&D shows only a moderate decrease. In a period of recession, firms either consider the risk of performing R&D to be higher, or are less willing to take risks (have higher risk aversion), or both. This has a large effect on the probability of participation, especially for smaller firms, while the spending intensity of firms conducting R&D is not affected very much.

Although not estimated directly, there is some indication that a fixed and sunk entry cost plays a role in the decision whether or not to engage in R&D, especially in the technologically less progressive industries. I estimate fixed cost a , divided by a term which, among other things, represents the profitability in case of success. For the Dutch (1988 and 1992) data, I do find this term (a^*) to be significantly positive (i.e. the fixed cost are not outweighed by the profitability in case of success) for the technologically less progressive Supplier Dominated and Scale Intensive industries, and not significantly different from zero in the technologically most progressive, the Science Based industry (the fixed cost are outweighed by a higher profitability in case of success). As far as there is in fact a fixed and sunk entry cost associated with performing R&D, this would also negatively affect the participation of smaller firms.

These results are in close agreement with what was found by Felder, Licht, Nerlinger and Stahl (1996). Based on an empirical study of the German manufacturing industry, they conclude that

"(..) the participation decision and the intensity decision are ruled by different mechanisms [which is one of the basic assumptions of the present model] respectively that fixed cost are associated with performing innovation activities."

I find a positive correlation between the disturbance terms of the participation and spending models, significant in two out of three cases. This implies that, next to the effect of a possible fixed and sunk entry cost, there is also an effect of the optimal level of the flow cost of R&D. A high level of optimal flow cost reduces the probability of participation. Also, in the presence of this positive correlation, small firm R&D is overestimated in OLS regressions on a restricted sample of firms performing R&D due to sample selection bias.

Cohen and Klepper (1996) maintain that the finding that R&D rises less than proportionately with firm size is caused by sample selection bias. My results confirm the presence of such a bias. However, in many other data bases the innovative activity of smaller firms is structurally underestimated because mainly formal R&D is considered, rather than the broad measure of R&D that I employ here. On balance, I find that in the Supplier Dominated, Scale Intensive, and Specialized Suppliers industries, the smaller firms that do engage in R&D, do so at a higher level of intensity. That is, they spend more per unit of firm size. According to the underlying model, and under the assumption that there are diminishing returns to scale in the selection of a development project, the fact that R&D expenditure increases less than proportionately with firm size means that, in these industries, smaller firms are more profit/cost efficient. Only in the Science Based industry, I find no significant difference in spending intensity between smaller and larger firms.

This conclusion is supported by more direct investigations of the relation between innovative outputs and inputs. For instance, Acs and Audretsch (1990) find on the basis of different US data bases that small firms contribute approximately 2.4 times more innovations per employee than do their larger counterparts. Also, in their 1991 study (Acs and Audretsch, 1991, p. 12-13) they find that:

"Combining individual firm records of R&D and innovative output over 700 enterprises, we are able to determine that, although larger firms may be more R&D-intensive than their smaller counterparts, the productivity of R&D apparently falls along with firm size (....) That is, the empirical evidence suggests that decreasing returns to R&D expenditures in producing innovative output exists."

Also, Brouwer and Kleinknecht (1996) find, based on their study of output indicators, that:

"(..) generally, larger firms have a higher probability to innovate. However, given that they innovate, smaller firms are certainly not less innovative than larger firms."

This is in close agreement with the above conclusion that smaller firms are more profit/cost efficient in innovation. There are however other, complementary explanations for the empirical finding that small firms have much more innovative output than one would expect on the basis of their innovative input. First, small firm R&D tends to be underestimated in many standard surveys, because mainly formal R&D, conducted in separate R&D-departments is measured (Kleinknecht and Reijnen, 1991). Moreover, studies of the different components of innovation costs indicate that larger firms have higher shares of R&D in total innovation costs than smaller firms (Archibugi, Evangelista and Simonetti, 1995; Felder, Licht, Nerlinger and Stahl, 1996), so that independently from the way it is measured, R&D would underestimate the innovative input of smaller firms. Second, the results of Acs, Audretsch and Feldman (1994) indicate that small firms more effectively take advantage of knowledge spillovers from corporate R&D laboratories and universities. And third, the economic value of innovations may differ between smaller and larger firms, as suggested by Cohen and Klepper (1992), who find theoretically that under certain stochastic conditions, larger firms will produce fewer innovations per dollar spent on R&D, but their innovations will be on average of a higher quality.

References

- Acs, Z.J. and D.B. Audretsch, 1990, *Innovation and Small Firms*, Cambridge: The MIT Press.
- Acs, Z.J. and D.B. Audretsch, 1991, 'R&D, Firm Size and Innovative Activity', in Z.J. Acs and D.B. Audretsch (eds.), *Innovation and Technological Change*, London: Harvester Wheatsheaf.
- Acs, Z.J., D.B. Audretsch and M.P. Feldman, 1994, 'R&D Spillovers and Recipient Firm Size', *Review of Economics and Statistics* **76**(2), 336-339.
- Amemiya, T., 1986, *Advanced Econometrics*, Oxford: Basil Blackwell.
- Archibugi, D., S.Cesaratto, G.Sirilli, 1991, 'Sources of Innovative Activities and Industrial Organization in Italy', *Research Policy* **20**, 299-313.
- Archibugi, D., R. Evangelista and R. Simonetti, 1995, 'Concentration, Firm Size and Innovation: Evidence from Innovation Costs', *Technovation* **15**(3), 153-163.
- Baldwin, W.L. and J.T. Scott, 1987, *Market Structure and Technological Change*, Chur: Harwood.
- Bound, J., C. Cummins, Z. Griliches, B.H. Hall and A. Jaffe, 1984, 'Who Does R&D and Who Patents?', in Z. Griliches (ed.), *R&D, Patents, and Productivity*, Chicago: University of Chicago Press.
- Brouwer, E. and A.H. Kleinknecht, 1994, *Innovatie in de Nederlandse Industrie en Dienstverlening (1992)*, Den Haag: Ministerie van Economische Zaken (Serie Beleidsstudies Technologie Economie, nr. 27).
- Brouwer, E. and A.H. Kleinknecht, 1996, 'Determinants of Innovation: A Micro-econometric Analysis of Three Alternative Innovation Output Indicators', in A.H. Kleinknecht (ed.), *Determinants of Innovation: The Message from New Indicators*, London: Macmillan Press.
- Cohen, W.M. and S. Klepper, 1992, 'The Anatomy of R&D Intensity Distributions', *American Economic Review* **82**(4), 773-799.
- Cohen, W.M. and S. Klepper, 1996, 'A Reprise of Size and R&D', *Economic Journal* **106**, 925-951.
- Crepon, B., E. Duguet and I. Kabla, 1996, 'Schumpeterian Conjectures: A Moderate Support from Various Innovation Measures', in A.H. Kleinknecht (ed.), *Determinants of Innovation: The Message from New Indicators*, London: Macmillan Press.
- Dasgupta, P. and J. Stiglitz, 1980, 'Uncertainty, Industrial Structure and the Speed of R&D', *Bell Journal of Economics II* **90**(1), 1-28.

- Dasgupta, P. and J. Stiglitz, 1981, 'Entry, Innovation, Exit', *European Economic Review* **15**, 137-158.
- Eisenhardt, K.M. and M.J. Zbaracki, 1992, 'Strategic Decision Making', *Strategic Management Journal* **13**, 17-37.
- Felder J., D. Harhoff, G. Licht, E. Nerlinger and H. Stahl, 1994a, *Innovationsverhalten der deutschen Wirtschaft: Ergebnisse der Innovationserhebung 1993*, Mannheim: ZEW-Dokumentation nr. 94-01.
- Felder J., D. Harhoff, G. Licht, E. Nerlinger and H. Stahl, 1994b, *Innovationsverhalten der deutschen Wirtschaft: Methodenbericht zur Innovationserhebung 1993*, Mannheim: ZEW-Dokumentation nr. 94-06.
- Felder, J., G. Licht, E. Nerlinger and H. Stahl, 1996, 'Factors Determining R&D and Innovation Expenditures in German Manufacturing Industries', in A.H. Kleinknecht (ed.), *Determinants of Innovation: The Message from New Indicators*, London: Macmillan Press, forthcoming.
- Kleinknecht, A.H. and J.O.N. Reijnen, 1991, 'More Evidence on the Undercounting of Small Firm R&D', *Research Policy* **20**, 579-587.
- Kleinknecht, A.H., J.O.N. Reijnen and J.J. Verweij, 1990, *Innovatie in de Nederlandse Industrie en Dienstverlening*, Den Haag: Ministerie van Economische Zaken (Serie Beleidsstudies Technologie Economie, nr.6).
- Lee, L.F., 1982, 'Some Approaches to the Correction of Selectivity Bias', *Review of Economic Studies* **XLIX**, 355-372.
- Lee, T. and L.L. Wilde, 1980, 'Market Structure and Innovation: A Reformulation', *Quarterly Journal of Economics* **94**, 429-436.
- Loury, G.C., 1979, 'Market Structure and Innovation', *Quarterly Journal of Economics* **93**, 395-410.
- Mood, A.M., F.A. Graybill and D.C. Boes, 1974, *Introduction to the Theory of Statistics*, 3rd. edn., Singapore: McGraw-Hill.
- Nooteboom, B., 1991, 'Entry, Spending and Firm Size in a Stochastic R&D Race', *Small Business Economics* **3**: 103-120.
- Pavitt, K., 1984, 'Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory', *Research Policy* **13**, 343-373.
- Townsend, J., F. Henwood, G. Thomas, K. Pavitt and S. Wyatt, 1981, *Innovations in Britain Since 1945*, Occasional Paper No. 16, Science Policy Research Unit, University of Sussex.
- Wyatt, S., 1985, 'Il Ruolo delle Piccole Imprese nell'attività innovativa: un'analisi del caso inglese', *Economia e Politica Industriale* **45**, 47-82.

Zelen, M. and N.C. Severo, 1965, 'Probability Functions', in M. Abramowitz and I.A. Stegun (eds.), *Handbook of Mathematical Functions*, New York: Dover Publications.