Research Cooperation and Research Expenditures with Endogenous Spillovers

Theory and Microeconometric Evidence for the German Service Sector

Ulrich Kaiser*

Centre for European Economic Research

and

Center for Finance and Econometrics at the University of Konstanz

January 2000

Abstract: This paper derives a three stage Cournot duopoly game for research collaboration, research expenditures and product market competition. The amount of knowledge firms can absorb from other firms is made dependent on their own research efforts, e.g., spillovers are treated as endogenous variables. It is shown that cooperating firms invest more in R&D than non–cooperating firms if spillovers are sufficiently large.

Incentives to cooperate increase with increasing market demand and decrease with increasing degrees of substitutability. Increases in market demand and in the generality of

*Helpful comments from Johannes Ludstek, and, most notably, from Georg Licht and François Laisney, are gratefully acknowledged.

This paper owes much to the ZEW's Mannheim Innovation panel team — namely to Günther Ebling, Sandra Gottschalk, Norbert Janz and Hiltrud Niggemann — for their ongoing effort to create the data based used in this paper and to Jürgen Moka for maintaining the ZEW's basic data bases. Paul Townsend provided an excellent proof–reading job.

This research was partially funded by the German Science Foundation (Deutsche Forschungsgemeinschaft, DFG) within the 'Industrial Economics and Input Markets' program.

the R&D approach lead to an increase in R&D effort.

The key findings of the theoretical model are tested using German innovation survey data for the service sector. A main finding from a simultaneous model for cooperation choice and innovation intensity is that innovation intensity decreases by 20 percent when research collaboration is started, with standard error of 5 percent.

Keywords: research cooperation, research expenditures, knowledge spillovers, simultaneous equation model, services

JEL classification: O31, L13, C24, C25

Address:

Ulrich Kaiser

Centre for European Economic Research

Department of Industrial Economics and International Management

P.O. Box 103443

D–68163 Mannheim, Germany

phone: +49.621.1235.292

fax: +49.621.1235.333

eMail: kaiser@zew.de

1 Introduction

In 1952, John Kenneth Galbraith noted that the 'era of cheap innovation' was over. He claimed that firms had exhausted low–cost R&D programs and were now forced to pool their R&D efforts in order to achieve scientific progress and to gain market powerS. Until the mid–eighties, however, antitrust law hampered firms' collaboration in the R&D process. More than 30 years passed by since Galbraith's statement before US and European governments considerably relaxed antitrust law to allow cooperative R&D.[1]

Starting points of this relaxation were the positive results from some Japanese and US–American research collaborations in the seventies and eighties. Spencer and Grindley (1993) argue that the R&D consortium SEMATECH contributed significantly to the leading position of the US in semiconductor industries. At least until the beginning of the Asian economic crisis in fall 1997, the influence of the MITI on industrial policy and industry–wide networks has been considered as having a positive impact on the Japanese success story (c.f. Miwa, 1996; Tsuru, 1994). Moreover, Jorde and Teece (1990) trace back the success of German mechanical engineering products in the seventies and eighties to the partly industrially financed research institutions.

For Germany, a strong increase in the number of research joint ventures (RJVs) can be observed. While only ten percent of all manufacturing firms in Germany were involved in R&D cooperations in 1971, 20 years later almost the half of all the firms in manufacturing industries conduct cooperative research (König et al., 1994). Based on US department

[1]Cornerstones of this development were the passage of the National Co–operative Research Act for the US in 1984 and the announcement of the block exception from Article 85 for certain categories of R&D agreements for the EEC in 1985. See Geroski (1993) for a discussion of these two antitrust law amendments.

of Justice data, Vonortas (1997) shows a sharp increase in the number of RJVs is also present in the US. The interest of economic policy in RJVs is still unchanged since R&D subsidies are increasingly often bound to joint R&D efforts.

Microeconomists began to develop theoretical frameworks to describe R&D expenditure and R&D cooperation in the mid–eighties. Pioneering contributions on R&D investment with spillovers are Brander and Spencer (1984), Katz (1986) and Spence (1986). A large strand of the younger literature is built on the pioneering contribution of D'Aspremont and Jaquemin (1988, 1990) who develop a two stage Cournot duopoly game for R&D expenditures under R&D cooperation, R&D competition and product market competition. Many subsequent papers adopted the structure of this model with modifications (Beath et al., 1988; Choi, 1993; DeBondt and Veugelers, 1991; De Bondt et al., 1992; Kamien et al., 1992; Salant and Shaffer (1998) Suzumura, 1992; Ziss; 1994).[2] In a recent contribution, Kaiser and Licht (1998) extend the D'Aspremont and Jaquemin model by analyzing both process and product innovation. They find that R&D expenditures have virtually the same structure for both product and process R&D.

A main question in all these paper is 'Does cooperative R&D increase or decrease R&D efforts?'. The common answer is: it depends on the amount of research spillovers created. Research spillovers arise whenever knowledge produced by firm i is voluntarily or

[2]A survey of the existing literature can be omitted here since there already exist extensive reviews by De Bondt (1996), Cohen (1995) and Geroski (1995). While the first author is mainly concerned with theoretical contributions to the literature, the latter summarize empirical findings. Also see the special issue of 'Annales d'Économie et de Statistique', vol. 49/50, on 'The Economics and Econometrics of Innovation' and the references cited therein.

involuntarily given to some other firm j without firm j having paid for it.[3].

If spillovers are sufficiently large, R&D investment under RJV exceeds that of competition. Intuitively, there are two opposing effects. Due to internalization of spillover — it is assumed that knowledge is fully exchanged in an RJV —, R&D investment is stimulated. Free–riding on the RJV partner's research effort may counteract the positive internalization effect.

Since there is scarce empirical evidence on the impact of RJVs on R&D investment, it remains merely an open question in empirical research to determine which effect is predominant. Earlier studies have found mixed results. Fölster (1995) shows for Sweden that governmental subsidies of R&D co–operations do not affect R&D investment in any direction. For SEMATECH, Irwin and Klenow (1996) find a reduction of R&D investment and an increase in profitability of SEMATECH members. For Germany, König et al. (1994) find a positive effect of cooperations on R&D investment for manufacturing. A positive impact of horizontal co–operations and horizontal R&D spillovers on the R&D intensity of German manufacturing firms is also shown by Inkmann (1999). While at least some empirical evidence exists on the relationship between R&D cooperation and R&D expenditure for manufacturing, to the best of my knowledge, nothing is known for the service sector. This paper adds to existing empirical studies in that it analyzes the service sector.

The theoretical part of this paper shares the essential features of the D'Aspremont and Jaquemin (1988, 1990) model. As in Kamien et al. (1992) and Suzumura (1992), how-

[3]Research spillovers from research institutions or from foreign countries are not considered here. See Mamuneas (1999) for a recent contribution to the first issue and Branstetter (1998) for a survey on the second topic.

ever, the D'Aspremont and Jaquemin framework is extended to explicitly model the R&D cooperation decision. Firms' R&D expenditure level, their R&D decision and their competition on the output market is modeled in a three–stages duopoly game. In the first stage, firms decide whether or not to conduct R&D in cooperation. In the second stage, they decide upon their R&D expenditures. Lastly, they compete in a Cournot–duopoly product market.

While in most existing studies R&D spillovers are assumed to be exogenously determined, they are treated as endogeneous in this paper. In fact, it appears to be unlikely that firms can gain from each other's knowledge independently of their own research effort. In traditional models, it is assumed that even a firm which does not invest in R&D at all gains from the stock of knowledge to an identical extent as another firm which spends a large amount of money on research.

The main findings of the theoretical model are that the impact of spillovers on firms' research efforts cannot be unambiguously determined and that an increase in the generality of the R&D approaches taken by a firm increases research efforts provided that the R&D approach is sufficiently general. An increase in the degree of substitutability between products creates disincentives to innovate under general conditions. An increase in market demand uniquely leads to increased incentives to both innovate and cooperate. The probability of cooperation increases with research approaches becoming more general. An increase in the degree of substitution effects the propensity to cooperate negatively.

The main implications of theoretical model are tested in the empirical part of this paper. Nesting logit models (van Ophem and Schram, 1997) are applied to disentangle empirically the determinants of R&D cooperation.[4] Three modes of cooperation are distingiushed:

[4] I call it a 'nesting' logit model since the approach of van Ophem and Schram (1997) nests the

vertical cooperation (cooperation with suppliers or customers), horizontal cooperation (cooperation with competitors) and non–cooperation.

In a last step, the paper aims at uncovering the impact of R&D cooperation on R&D expenditures. Since firms may simultaneously decide upon R&D cooperation and R&D expenditure, a simultaneous model for the cooperation and the expenditure decision is run.

I test if there are differences in the determinants of research efforts for cooperating and non–cooperating firms by applying Minimum Distance Estimation. The empirical findings are broadly consistent with the theoretical model. A central result from the empirical investigation is, however, that innovation cooperations tend to decrease own innovation efforts. On average, the effect amounts to a decrease by 20 percent with a standard error of 5.13 percent. Other results are that an increase in market demand and in the amount of horizontal spillovers significantly increase innovation efforts. Positive, though insignificant, effects of both vertical and horizontal spillovers are found for the decision to cooperate.

2 Theoretical model

2.1 Market demand

In order to keep things tractable and interpretable, this paper deals with process innovation only. With regard to the empirical tests of the main theoretical conclusions, this is not a major drawback since the data set applied here does not differentiate between prod-

multinomial, the traditional and the sequential logit model as special cases.

uct and process innovation.[5] In Kaiser and Licht (1998), we consider both process and product R&D in a Cournot oligopoly framework with exogenous spillovers.[6] We show that the optimality conditions for product and process R&D have virtually the same structure and that results obtained for product R&D are qualitatively also valid for process R&D. The theoretical models of this and the earlier paper follow D'Aspremont and Jaquemin (1988, 1990).

For other theoretical models distinguishing between vertical and horizontal cooperation, see Harhoff (1996), Inkmann (1999) (1992) and Peters (1995, 1997). For a discussion of the optimal RJV–size, see Poyago–Theotoky (1995). An empirical discussion of the stability of RJVs is provided by Kogut (1989).

By decreasing production cost, process innovations improve a firm's supply conditions. Models of process R&D are primarily based on systems of linear demand functions. I assume that there are two firms and Z households in the economy. The budget restriction of a household is

$$M = Y - \sum_{i=1}^{2} p_i q_i, \tag{1}$$

where M indicates the part of the households income spent on goods not affected by cross–price effects.[7] The household utility function to be maximized is assumed to be

[5]As it has become apparent from case studies undertaken in the context of the Mannheim Innovation Panels (Licht et al., 1997), especially service sector firms find it difficult to even judge whether a particular innovation is a product or a process innovation. It is easy to imagine that it even more difficult to assess the expenditure for product and process innovation.

[6]Earlier contributions discussing product innovations are Beath et al. (1987), Choi (1993), DeBondt and Kesteloot (1993), Levin and Reiss as well as Motta (1992).

[7]However, consumers will adjust M in order to meet the budget constraint if an innovation takes

given by

$$U(q_1, q_2) \; = \; \sum_{i=1}^{2}(q_i - q_j^2) \; - \; 2\sigma q_i q_j \; + \; M. \tag{2}$$

This utility function is consistent with the standard utility function used, i.a., by Sutton (1998) in a Cournot–framework or by Deneckere and Davidson (1985) in a Bertrand competition context. The parameter σ is a measure of substitutability of the two goods with $\sigma \in [-1, 1]$. If $\sigma = 1$, the two goods are perfect substitutes and if $\sigma = -1$, they are perfect complements. The extreme case of monopoly is present if $\sigma = 0$. The utility function has the usual properties. Market demand for good i is represented by the sum of individual demands of the Z identical consumers. Household demand for good q_i is derived from the first order conditions optimal household demand. Defining $2/Z = b$, the demand for good q_i is given linear market demand function:

$$p_i \; = \; 1 \; - \; b\sigma q_j \; - \; bq_i, \tag{3}$$

where the quantities q_i and q_j now denote market demand instead of individual demand. As apparent from equation (3), an increase in market demand, i.e., an increase in the number of consumers, shifts and turns out the demand function out to the right.

2.2 R&D production function

Following the tradition of R&D cooperation models (c.f. Kamien et al., 1992), market structure is modeled as a Cournot game in which firms can decrease production cost by conducting R&D. R&D efforts do not only contribute to a reduction of own production cost but also spill over to competitors, customers or suppliers. R&D performing firms,

place.

however, have the possibility of conducting R&D in cooperation with other firms. In this case, results of R&D are assumed to be fully exchanged. By performing cooperative R&D, firms can internalize the externalities related to the R&D process.

The deterministic R&D model suggested here falls short of real innovation processes which are driven by risk and irreversibilities.[8] It also is somewhat ahistorical as neither a modeling of the intertemporal investment decision nor past R&D investment decisions are incorporated. The model introduced here is merely related to a sequential 'trial and error' process.

This model of R&D cooperation and R&D expenditure is very similar to that of Kamien et al. (1992). The main difference of my model in comparison to most existing models for R&D cooperation and R&D expenditures lies in the incorporation of endogenous spillovers.

With the recent exception of Kamien and Zang (1998), most existing papers assume the amount of knowledge spilling over from firm i to firm j to be exogenously determined.[9] This is somewhat unrealistic since a firm's ability to internalize other firms' knowledge is likely to directly depend on its own stock of knowledge (Cohen and Levinthal, 1989; Cohen and Levinthal, 1990; Levin, 1988; Levin et al., 1987). Further, if spillovers are treated as exogenously given, the decision to invest in R&D is conflated with the decision

[8] Beaudreau (1996) discusses a model that takes in to account the uncertainty and multidimensionality without, however, finding markedly different results compared to contributions based on the D'Aspremont and Jaquemin (1988, 1990) framework.

[9] Other exceptions are the contributions of Katsoulacos and Ulph (1998a and 1998b). In their model, the extend of information sharing in an RJV is determined endogenously. Gersbach and Schmutzler (1999) endogenize spillovers by making a firm's absorptive capacity dependent on its success in the competition for other firms R&D personnel.

on the extent of information sharing. In turn, the decision on the extent of information sharing is conflated with the decision on R&D cooperation. In this case, to distinct market failures cannot be distinguished from one another: the market failure related to the R&D investment level and the market failure associated with the level of information revelation. The main assumptions on production techniques, R&D spillovers and R&D production functions are briefly introduced below. The production conditions are captured by a linear marginal cost function k_i. By conducting R&D, firms can decrease marginal costs. Denoting X_i the *effective* level of R&D of firm i, the marginal cost function for firm i is assumed to be given by:

$$k_i \ = \ c_i \ - f(X_i). \tag{4}$$

It is required that

$$f(0) = 0, \ f(X_i) \leq c, \ f'(X_i) > 0, \ f''(X_i) < 0, \tag{5}$$

$$lim_{X_i \to \infty} \ f'(X_i) \ \to 0 \text{ and } (1 - k_i) f''(X_i) + f'(X_i)^2 < 0.$$

Expression $f(X_i)$ denotes the production function of process innovations. The assumptions with respect to level and form of the R&D production function make sure that it pays for all firms to conduct R&D. The last expression in equation (5) assures that R&D cost show a steeper increase than the returns to R&D.

Following Kamien and Schwartz (1998), firm i's effective R&D is assumed to be given by

$$X_i \ = \ x_i \ + (1 - \delta) \ \beta \ x_i^{\delta} x_j^{1-\delta} \tag{6}$$

with $\delta, \beta \ \in (0, 1)$.[10] The parameter β denotes the exogenously given intensity of R&D spillovers. If firm i does not invest in R&D at all, it cannot receive any spillovers from

[10]In the original paper by Kamien and Schwartz (1998), firms decide upon the value of δ in an additional stage of a Cournot oligopoly game.

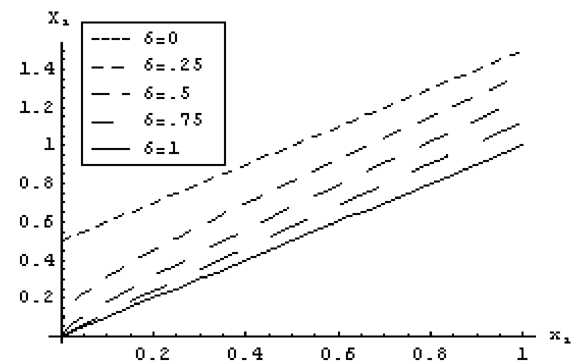
other firms research efforts. The parameter δ denotes firm i's "R&D approach" (Kamien and Schwartz, 1998, p. 3). That is, if $\delta = 1$, firms are both universal recipients from and universal donors of other firm's R&D efforts. Firm i's effective R&D function then reduces to the standard formulation of effective R&D (e.g., Beath et al. (1998), D'Aspremont and Jaquemin (1988, 1990), DeBondt and Veugelers (1991), Kaiser and Licht (1998), Kamien et al. (1990), Poyago–Theotoky (1995), Röller et al. (1998) and Spence (1984)) for duopolies, $X_i = x_i + \beta x_j$.

At the other extreme, with $\delta = 0$, effective R&D is equal to own R&D. Then, firms are neither able to internalize any of the other firms' knowledge nor do they contribute to other firm's effective R&D. If δ is in between the two extreme cases, effective R&D is homogeneous of degree one in x_i.

Firm i's absorptive capacity is represented by $(1-\delta)x_i^{\delta_i}$, which is increasing and globally concave in both x_i and x_j. If $\delta\ <(>)\ 1-\ 1/ln(x_i)$, firms absorptive capacity is increasing (decreasing) in δ. The function is globally concave (convex) in δ if $\delta\ <(>)\ 1-\ 2/ln(x_i)$. Other firms' R&D effort increases the marginal productivity of own R&D.

Figure, 1 depicts firms' effective R&D functions, X_i, for firm j's research efforts set to one and exogenous spillovers set to .5 under alternative research expenditures of firm i, x_i. In Figure 2, the shape of the effective R&D function under alternative values of δ is shown for various combinations of own and the other firm's research efforts.

Fig. 1. Shape of firm's effective R&D function, X_i, as a function of firm i's own research efforts under alternative values of δ. Exogenous spillovers, β, are set to .5, firm j's research efforts are assumed to be 1.


X_1
δ=0
δ=.25
δ=.5
δ=.75
δ=1
1.4
1.2
1
0.8
0.6
0.4
0.2
0.2
0.4
0.6
0.8
1
x_1

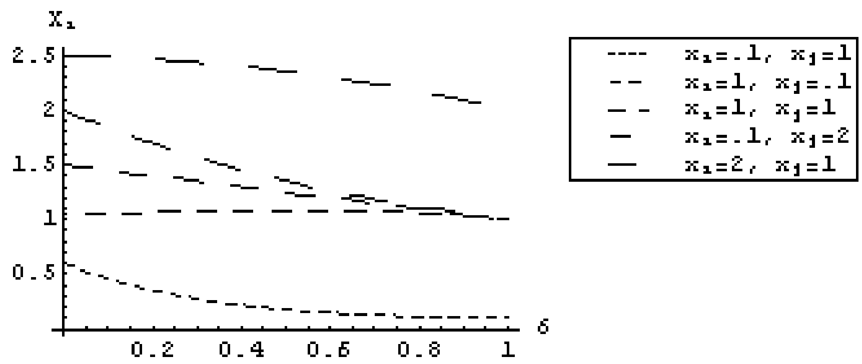


Fig. 2. Shape of firm's effective R&D function, X_i, as a function of the generality of the R&D approach, δ under alternative own and the other firm's research efforts, x_i and $'_j$. Exogenous spillovers, β, are set to .5.

2.3 Stage III: Product market competition with R&D expenditures given

The R&D oligopoly game is solved by backwards induction. In stage III of the game, the two firms choose the optimal level of output given parametrically sunk cost. Collusive agreements concerning the level of output are ruled out. Firms maximize their profits, Π, independently by choosing the optimal level of output q_i:

$$max_{q_i}\ \Pi_i \ = \ (p_i - k_i)q_i \ - \ x_i. \tag{7}$$

Optimal output is derived by using the Cournot assumption and is given by

$$q_i^* \ = \ \frac{(1-k_i) + \frac{\sigma}{2-\sigma}\Big((1-k_i) - (1-k_j)\Big)}{b(2+\sigma)}. \tag{8}$$

This implies that in a symmetric equilibrium, own output is increasing in own R&D effort if a sufficiently general R&D approach is present: $\delta > \sigma/(2+\sigma)$. If this condition is not met, e.g., the R&D approach is less general, own output is increasing in own R&D if spillovers are small. An increase in firm j's R&D efforts leads to an increase in firm i's output if (i) exogenous spillovers are small and firms follow a general R&D approach *or* (ii) exogenous spillovers are large and firms follow a specialized R&D approach. Under conditions (i) and (ii), the initial improvement of the relative position of firm j due to its increase in R&D efforts is counteracted by the spillover–induced improvement of the relative position of firm i. This indicates incentives to cooperatively conduct R&D.

The differences to the case of truly exogenous spillovers ($\delta = 0$) as in Kaiser and Licht (1998) are striking. For $\delta = 0$, an increase in the other firm's R&D effort increases own output if $\beta > \sigma/2$.

It can further be shown that an increase in the degree of substitutability leads to a decrease in own output. Therefore, incentives to form a research joint ventures should differ with the type of cooperation partner (horizontally related/vertically related partners).

Comparative–static analysis further shows that own output increases with market size and decreases if more general R&D approaches are chosen.

2.4 Stage II: Determination of R&D level

In the second stage of the game, firms maximize profits by optimally choosing R&D efforts. If firms decide not to cooperate in R&D in the first stage of the game, firm i's profit function is given by the difference between total sales, $TS_i = b\ q_i^2$ and R&D expenditures:

$$max_{x_i}\ \Pi_i \ = \ TS_i \ - \ x_i, \tag{9}$$

In a symmetric equilibrium, where firm subscripts can be omitted, optimal R&D expenditures follow from:

$$f'(X^c)(1-c+f(X^c)) \;=\; \frac{b(2-\sigma)(2+\sigma)^2}{2\Big(2+\beta(1-\delta)(\delta(2+\sigma)-\sigma)\Big)}, \tag{10}$$

where X_i^c denotes effective R&D of firm i under separate profit maximization (Cournot). If firms decide to cooperate in R&D in the first stage of the game, they maximize joint profit over their R&D efforts:

$$max_{x_i}\ \Pi_i \;=\; TS_i \;-\; x_i \;+\; S_j \;-\; x_j, \tag{11}$$

which leads to the following first–order–condition:

$$f'(X^{jv})(1-c+f(X^{jv})) \;=\; \frac{b(2+\sigma)^2}{2\Big(1+\beta(1-\delta)\Big)}, \tag{12}$$

where X_i^{jv} denotes effective R&D expenditures under joint profit maximization.

Under RJV — as, i.e., in Beath and Ulph (1989), Motta (1992), Crepon et al. (1992) and Choi (1993) — full information sharing is assumed, β takes on the value 1. The impact of spillovers on R&D expenditures under R&D competition is ambiguous. It is positive if $(\delta(2+\sigma)-\sigma)(1-k^c)+x^c(2+\beta(1-\delta)(\delta(2+\sigma)-\sigma)(f[X^c]^2+(1-k^c)f[X^c]'')>0$ and negative otherwise.[11]

The consequences of research collaboration for the level of R&D expenditures in the case of R&D cooperation can be drawn from comparing equations (12) and (10). For sufficiently large spillovers, e.g.,

$$\beta \;>\; \frac{(2-\sigma)(2-\delta)-2}{(1-\delta)(\delta(2+\sigma)-\sigma)}, \tag{13}$$

[11]Note the difference for $\delta=0$: under exogenous spillovers, the impact of an increase in exogenous spillovers on R&D expenditures is unambiguously negative if goods are substitutes, e.g., if firm conduct substitutive research.

R&D efforts are larger under RJV than under Cournot competition. Condition (13) is always satisfied for general R&D approaches, $\delta > 2 - 2/(2-\sigma)$.

Other results from comparative–static analysis of equations (10) and (12) are that (i) for sufficiently general R&D approaches, an increase in the generality leads to an increase in research efforts both under RJV and competition, (ii) an increase in the degree of substitutability has a disincentive effect on research efforts,[12] (iii) an increase in market demand leads to an increase in research efforts both under RJV and competition.

2.5 Stage I: R&D cooperation

Incentives for firms to cooperatively conduct R&D become apparent from comparing the level of profits firms earn with and without cooperation. If a RJV is started, each firm i have to face setup cost $C(\delta, x_i)$ (e.g. organization cost, informational exchange cost) which are assumed to depend negatively with the generality of the R&D approach and with own innovation expenditures. A RJV is started if:

$$\Pi_i^{jv} - \Pi_i^c = S_i^{jv} - x_i^{jv} - C(\delta, x_i) - S_i^c + x_i^c > 0. \tag{14}$$

Both profit functions are globally concave in x_i as long as conditions (5) hold. Incentives to start a research joint venture increase with increasing differences in profits.

Comparative–static analysis of equation (14) shows that an increase in exogenous spillovers, β, leads to an increase in the probability of RJV formation if

$$\epsilon_{x_i,\beta} > \frac{\epsilon_{S_i,x_i} \frac{(1-\delta)\beta}{1+\beta(1-\delta)}}{\frac{x_i}{S_i} - \epsilon_{S_i,x_i}} \tag{15}$$

and if $\partial S_i/\partial x_i < 1$. If $\partial S_i/\partial x_i > 1$, the elasticity of R&D expenditures with respect to exogenous spillovers, $\epsilon_{x_i,\beta}$ needs to be smaller than the right–hand term of equation

[12]For research efforts under competition, this only holds for $\sigma < 2/3$.

(15) to guarantee an increasing RJV formation probability to to an increase in exogenous spillovers. The expression ϵ_{S_i,x_i} denotes the elasticity of sales with respect to R&D expenditures.

Increases in the generality of the R&D approach and in market demand both lead to incentive to cooperate in R&D. An increase in the degree of substitutability creates disincentive effects for RJV formation. This indicates that RJV should be more widespread between vertically than between horizontally related firms.

2.6 Main findings of the theoretical model

The results obtained from the theoretical model can be summarized as follows:

(1) Cooperations should be more widespread between vertically related firms than between horizontally related firms.

(2) If spillovers are large, R&D expenditures are larger under RJV than under R&D competition.

(3) An increase in market demand leads to increased R&D expenditures both under RJV and Cournot competition.

(4) An increase in the generality of the R&D approach leads to an increase in R&D expenditures for both R&D competition and R&D joint venture provided that the R&D approach already is sufficiently general.

(5) The effect of exogenous spillovers on R&D efforts is ambiguous.

(6) The effect of exogenous spillovers on RJV fromation is ambiguous.

(7) The more general R&D approaches are, the more likely it is that RJVs are formed.

(8) An increase in market demand creates incentives to form a RJV.

(9) An increase in the degree of substitution creates disincentives to form a RJV.

(10) If the degree of substitution between products is sufficiently low, an increase in the degree of substitution has a disincentive effect on research efforts.

In the remainder of this paper, it will be empirically tested if findings (1)—(8) from the theoretical model are supported by the estimation results.

3 Data and empirical implementation

The most striking difference between the stylized theoretical model developed in the preceding sections and the real–world is the duopoly assumption. Accordingly, the empirical investigation is based on a data set of firms competing in multi–firm markets and thus fails to replicate the theoretical model. However, in order to smooth the difference between the theoretical model and the data studied, the estimations include various control variables for observable firm heterogeneity.

The empirical analysis is based on the first wave of the MIP–S, which is collected by the ZEW, the Fraunhofer Institute for Systems and Innovation Research and infas–Sozialforschung on behalf of the German ministry for education, research, science and technology. This data set was originally collected in order to analyze the innovation behaviour of the German service sector. It is thoroughly described in Janz and Licht (1999). The MIP–S is a mail survey. Its first wave was designed and conducted in 1995. The survey's population refers to all firms with more than four employees. The survey design extends the traditional concept of innovation surveys in manufacturing industries as summarized in the OECD Oslo-Manual (OECD, 1994) to the service sector. Information collected includes (1) general data on the participating firms such as firm size, skill mix, sector affiliation, sales, exports, (2) innovation activity and innovation expenditures, (3) labor and training cost, (4) investment in new technologies and other physical assets, (5) factors hampering innovation and (6) information sources for innovation.

Basic methodological issues are described in the OSLO-manual (OECD, 1994). The description presented here thus concentrates on the variables used in the estimations and omits any further details on the data set.

Cooperation in innovation

The MIP–S does not contain information on R&D cooperation but on innovation cooperations. Since the theoretical model developed in the preceding sections is applicable to both R&D and innovation cooperation, the lack of information on R&D cooperation is not a major drawback for the empirical study.

Innovation cooperation is defined as "cooperation, in which the partners actively take part in joint innovation projects". It is stressed that innovation cooperation — as opposed to commissioned research — involves "joint active research work". Firms which answer to this general question in the MIP–S questionnaire with 'yes' can then choose from a list of possible cooperation partners where multiple responses are allowed: (1) customers, (2) suppliers, and (3) competitors. The questionnaire allows for multiple responses concerning cooperation partners and does neither provide information on the number of RJVs a firm is involved in nor on the total number of research projects pursued within the firm. It also not asked for the amount of money spent on individual research projects. These shortcomings should be taken into account when interpreting the results.

R&D expenditures

The MIP–S does not contain information on R&D expenditures. Therefore, I proxy R&D effort by innovation expenditures. This is probably a quite good proxy variable for services since services firms do often not conduct R&D but invest a large share of their sales in innovation (Janz and Licht, 1999). In the MIP–S questionnaire, innovations are defined as follows: "We understand innovations as new or markedly improved services which are offered to your customers, or new or markedly improved processes in the production of services which are introduced in your firm."

Spillover pools

The level of innovation expenditures constitutes the basis for the construction of the spillover pools. Since from the discussion of the impact of the degree of substitution between products it has become clear that incentives to cooperate and to invest in innovation differ with the type of cooperation partner. Therefore, the empirical model differentiates between horizontal and vertical types of cooperation and hence also distinguishes between horizontal and vertical spillovers. The spillovers firm i receives can be regarded as the empirical implementation of β of equation (6). This expression is proxied by

$$S_i = \sum_{j \neq i}^{N} \omega_{ij}\ x_j, \tag{16}$$

where ω_{ij} denoted firm i's absorptive capacity. It is the fraction of innovation investment of firm j which virtually spills over to firm i. Horizontal spillovers are calculated by summing over all firms inside firm i's own sector while vertical spillovers are obtained by summing over all firms outside the own sector. In this study, spillovers from both the service and the manufacturing sector are considered.[13]

Numerous suggestions on how to calculate the spillover parameter ω_{ij} can be found in the literature. The formulation of the amount of knowledge becoming appropriable to firm i from firm j, $(1-\delta)\ \beta\ x_i^{\delta} x_j^{1-\delta}$ and which, jointly with firm i's on research effort, constitutes firm i's effective R&D level (equation (6)) already suggests that the extent to which knowledge spills over from one firm to the other depends on the similarity between firms in the type of technology they use. In fact, most of the approaches to proxy ω_{ij} are based on firms' distances in 'technology space' as Jaffe (1988) calls it.

In a recent contribution, Kaiser (1999) reviews frequently applied methods to proxy ω_{ij} and tests them against one another. He finds that the uncentered correlation of firm characteristics related to the type of technology they use in production proxies ω_{ij} best out of the approaches considered. This approach is due to Jaffe (1986 and 1988), who uses patent citation data to approximate knowledge flows between industries.[14] His assumption is that knowledge flows between industries a and b are proportional to the share of patents of industry b in the area of industry a. Jaffe (1986 and 1988) applies this basic idea to firm–level data. He defines k–dimensional patent distribution vectors, $\boldsymbol{f}$, whose elements are the fractions of firm j's research efforts devoted to its k most important fields of patent activity. His measure of technological distance between firm i and firm j is the uncentered correlation between $\boldsymbol{f_i}$ and $\boldsymbol{f_j}$:

$$\omega_{ij} \;=\; \frac{\boldsymbol{f_i}'\boldsymbol{f_j}}{\Big((\boldsymbol{f_i}'\boldsymbol{f_i})(\boldsymbol{f_j}'\boldsymbol{f_j})\Big)^{\frac{1}{2}}}, \tag{17}$$

[13] I used the Mannheim Innovation Panel in Manufacturing (MIP–M) as a complementary data source. See Kaiser and Licht (1998) or Janz and Licht (1999) for details on this data set.

[14] Jaffe's method is an extension of Scherer's (1982 and 1984) idea to use patent data as a measure for knowledge flows between industries.

the cosine($\boldsymbol{f_i}$, $\boldsymbol{f_j}$). If firm i's and firm j's patent activity perfectly coincide, ω_{ij} takes on the value 1. If they do not overlap at all, it takes on the value 0. Jaffe's measure of technological distance suffers from the same drawback as the approaches by Scherer (1982 and 1984) since, as Griliches (1990, p. 1,669) points out: "Not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in 'quality' (...)."[15] Although Griliches' remark only matters if the ratio of patented to unpatented inventions varies across the economic units under consideration, the shortcoming that "not all inventions are patented" is especially binding in the services sector where innovation is often tied to tacit knowledge which cannot be patented. Instead of filling the $\boldsymbol{f}$–vector with patent citation data, I fill it with the following a priori chosen variables which I think represent technological proximity between firms best: the shares of high (university and technical college graduates), medium (workers with completed vocational training) and unskilled labor in total workforce, expenditures for continuing education and vocational training of the employees (per employee), labor cost per employee, investment (scaled by sales) and five variables summarizing five main factors hampering innovative activity.[16]

For the construction of the latter five variables I applied a factor analysis on the 13 possible answers to the following question asked in the MIP questionnaires: "Please indicate the importance of the following factors hampering your innovative activity on a scale from 1 (very important) to 5 (not important)." The possible answers include (1) high

[15]Pavitt (1985 and 1988) comments on the usefulness of patent statistics as indicators for economic activity. See Arundel and Kabla (1998) and Brouwer and Kleinknecht (1999) for estimates of patent propensities.

[16]These are, however, measures of firm characteristics rather than measures of technological distance in a strict sense.

risk with respect to the feasibility of the innovation project, (2) high risk with respect to market chances of the innovation, (3) unforeseen innovation cost, (4) high cost of the innovation project, (5) lasting amortization duration of the innovation project, (6) lack of equity, (7) lack of debt, (8) lack of qualified personnel, (9) lack of technical equipment, (10) non–matured innovative technologies, (11) internal resistance against innovations, (12) lasting administrative/authorization processes and (13) legislation. From the factor analysis of the questions five main factors can be identified which I call 'risk' (consisting of questions (1), (2) and (3)), 'cost' (questions (4)—(5)), 'capital' (questions (6)—(7)), 'intern' (questions (9)—(11)) and 'law' (questions (12)—(13)). I use total factor scores scaled by the maximum total score for each of the three variables. E.g., if firm i indicates that lack of equity is of high importance (score=5) and indicates that lack of debt is of no importance (score=1), the total score for factor 'capital' is $5 + 1 = 6$ and the variable eventually used takes on the value $0.6 = 6/(5 + 5)$.

Horizontal spillovers are denoted by S^h, vertical spillovers are denoted by S^v. In order to distinguish between horizontal and vertical spillovers, I aimed at obtaining quite narrowly defined sectors. In the construction of the spillover pools, I differentiate between 115 sectors, there are 66 for manufacturing and 49 for services. At least ten firms are situated in each of these sectors. Details and a thorough discussion on the way the spillover pools are constructed as well as descriptive statistics are presented in Kaiser (1999).

Indicators for the generality of the R&D approach

The construction of the empirical counterpart of δ is based on the assumption that the more basic, e.g., the more general a firm's research approach is, the more it can gain from science in its innovation process.[17] In turn, if the more information source are used in the innovation process, the more idiosyncratic is the R&D approach. The MIP–S contains a question on information sources for the innovation process. Firms were asked to indicate on a five point scale ranging from 'not important at all' to 'very important' how important the following information sources were in the innovation process: (1) customers, (2) suppliers, (3) competitors, (4) universities and technical colleges, (5) public research institutions, (6) fairs and exhibitions and (7) the patent system. A canonical correlation analysis was conducted to find common factors of these information sources. Based on findings by Kaiser and Licht (1998), it was checked whether customers, suppliers and competitors as 'private' information sources can be lumped together and whether universities, public research institutions, fairs and the patent system as 'scientific' information sources can be grouped together. The results of the canonical correlation broadly support my guess as shown in Appendix A. The reported linear combinations for the two factors are calculated on a NACE–Rev.1 two digit sectoral level in order to avoid potential endogeneity problems with innovation expenditures and are denoted by $SCIENCE$ (scientific information sources) and $PRIVATE$ (private information sources), respectively.

Market demand

In the theoretical model it has been shown that an increase in market demand, e.g., an increase in the number of households Z, has a positive effect on R&D expenditures. The effect of an increase in market demand on RJV formation is ambiguous. Market demand is considered in the empirical model by firms' export shares, EXS, since a expansion

[17] I hereby somewhat follow the idea pursued by Levin and Reiss (1988) who assume that sectors closely related to science stay at the beginning of their development so they find themselves in an area of the production function with high marginal returns.

to a foreign market is equivalent to an increase in market demand. Changes in market demand are also captured in the empirical model by a set of dummy variables which represent changes in total sales on an ordinal scale. In the MIP–S, firms were asked for an assessment of their sales development over the past three years. The assessment ranged from strong decrease to strong increase on a five–point scale. The dummy variable for strong decrease takes on the value 1 if strong decrease was indicated and zero otherwise. It is denoted by $SALES--$. The other dummy variables for decrease, increase and strong increase in sales are constructed accordingly. They are denoted by $SALES-$, $SALES+$ and $SALES++$, respectively.

Controls for observable firm heterogeneity

The sample used here includes firms of all sectors of services as well as firms of different sizes. I attempt to take into account the resulting firm heterogeneity by introducing various control variables.

In order to capture the heterogeneity of product market conditions, a diversification index, denoted by $DIVERS$ is included in the estimations. It is constructed from firms' answers to a MIP–S question on the sales share of (1) customers from the producing sector, (2) customers from the services sector, (3) the state and (4) private households as

$$DIVERS_i = \frac{1}{\sum_{l=1}^{4} share_{l,i}^2}, \qquad (18)$$

where $share_{l,i}$ denotes the share of the lth customer group in total sales of firm i. The larger this index is, the more the firm is diversified.

This variable is included in the innovation expenditure equation since more diversified firms are able to apply innovation findings to a broader product range.

In order to further control for observable firm heterogeneity, the natural logarithm of the number of employees and its square are included in the specification. Further, three sector class dummy variables for business–related services (tax and business consultancy, architectural services, advertising, labor recruiting, industrial cleaning, BRS) trade ($TRADE$) and transport ($TRANS$) are included. I further include a dummy variable $EAST$ for East German firms.

Descriptive statistics of the variables used in empirical model are presented in Appendix B.

4 Results

Due to the complexity of the theoretical model, it is not possible to structurally estimate the equations derived there. Instead, I test the main hypotheses of our theoretical model as summarized in section 2.6.

How can our theoretical model be implemented empirically? My empirical analysis proceeds in three steps. First, I analyze firm's cooperation choice. Though it is not modeled explicitly in the theoretical model, it has become apparent that incentives to cooperate should differ with the cooperation partner. Therefore, the empirical approach of my first step in the empirical investigation does not only analyze the initial cooperation decision but also the choice of vertical or horizontal partners. Second, I investigate the determinants of firm's research investment intensity (innovation investment scaled by sales). Since firms may simultaneously choose their research efforts and research collaboration, the econometric approach takes this potential simultaneity into account. Lastly, I compare the determinants of innovation intensity under RJV and research competition by applying a Minimum Distance Estimation (MDE).

4.1 Cooperation decision

In the theoretical model described above, it pays for all firms to invest in innovation. Hence, I only consider those firms which actually invest in innovation although the sample also contains 541 firms which do not invest in innovation. Further, the MIP–S not only contains information on whether a firm is involved in innovation cooperations, it also contains information on whether a firm conducts joint R&D horizontally (with competitors), or vertically (with customers and/or suppliers). Since firms may be involved in both horizontal and vertical cooperations, a third possibility exists which I call a 'mixed' cooperation.

Figure 3 summarizes the decisions a firm has to reach in its R&D cooperation decision making process. In a first stage, the firm decides whether or not to conduct R&D cooperatively. If it has decided to do joint R&D, it then has to reach a decision between horizontal, vertical or mixed cooperation in a second stage. In a third stage firms decide upon their level of R&D spending, given their cooperation decision.

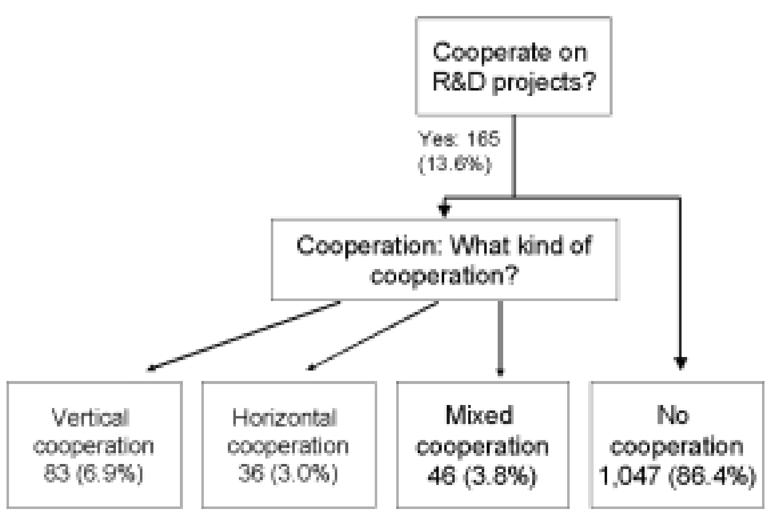


Fig. 3. Population of the alternative cooperation modes in absolute (relative) terms.

Figure 3 shows that the category 'horizontal' cooperation is thinly populated, both in absolute terms and in relation to the other choices. We therefore combine the horizontal choice and the 'mixed' cooperation mode.[18]

It is important to note that the representation by a decision tree as in Figure 3 is of purely analytical nature. It is not implied that time actually passes by between the individual decisions since "one must distinguish between hierarchical behavior and hierarchical structure for the mathematical forms of the choice probabilities" (Pudney, 1989, p. 125). In fact, choosing the appropriate econometric model for such a discrete choice problem is difficult. If time actually passed by between the decision stages, a sequential model would be appropriate. If the lower stage mattered in the decision making process of the first stage, a nested multinomial logit (NMNL) model should be used. If firms decided simultaneously upon R&D cooperation and the type of cooperation partner, a multinomial logit model (MNL) would be appropriate.[19] It thus is desirable to have a flexible econometric technique at hand which nests these types of discrete choice models. Such an estimator has been prosed by van Ophem and Schram (1997) who show that the simultaneous and the sequential logit model can be combined without loosing the properties of the logit model. The sequential, the NMNL and the MNL are nested by a single parameter, κ. The interpretation of this parameter is close to the interpretation of the coefficient corresponding to the inclusive value in NMNL models: For $\kappa = 0$, the utilities of the lower stage in a decision process do not determine the utilities in the upper stages so that the model could be sequentially estimated. If $\kappa = 1$, the decision reached in the upper stage

[18]See Blundell et al. (1993) for a theoretical reasoning of combining choice categories.

[19]See Eymann (1995) for a detailed discussion of these types of models and empirical examples.

is determined by the maximum utility to be obtained in the lower stage leading to the MNL as appropriate econometric tool. If $\kappa \in (0, 1)$, an intermediate position is obtained and the NMNL is appropriate.

The estimator suggested by van Ophem and Schram (1997) does — as opposed to the traditional NMNL where the parameter related to the inclusive value is bounded within $(0, 1)$ — allow for values of κ outside the (0,1) range on statistical grounds. However, for $\kappa > 1$ or $\kappa < 0$, there is no economic interpretation. Technical details of the van Ophem and Schram (1997) estimator are presented in Appendix C.

The empirical model of cooperation choice includes the following variables: horizontal and vertical spillovers, S^h and S^v, the R&D productivity proxies $PRIVATE$ and $SCIENCE$, export share as a market demand indicator, EXS, a dummy variable $EAST$ for East German firms, the natural logarithm of firm size and its square, $LSIZE$ and $LSIZE^2$ as well as two sector affiliation dummy variables $TRANS$ and BRS (business–related services).

Estimation results of the cooperation choice are presented in Table 1. This table contains beside the estimated coefficients and the related standard error also the marginal effect of a one percent change of the related variable on the choice of the cooperation modes. The results displayed in Table 1 are, however, somewhat unsatisfactory since the precision of the estimates is low as indicated by low t–values. Therefore, only tentative conclusions can be drawn from the estimation results: by and large, spillovers appear to have a positive impact on RJV formation. Proximity to both scientific and private information sources tends to increase the probability of RJV formation. The effect of scientific information sources on RJV formation, the proxy variable for δ is highly significant. Firms from the transport sector tend to form RJVs significantly more often than business–related services firms and firms from trade.

The impact of horizontal spillovers on the probability to cooperate in a mixed mode is positive and significant at the ten percent significance level. Proximity to science appears to decrease firms' propensity to cooperate in a mixed mode.

The goodness–of–fit of the specification displayed in Table 1 is modest. The McFadden (1974) Likelihood ratio index is .06, the McFadden Likelihood ratio index with the Aldrich and Nelson (1989) correction for the number of observations being applied is .056. Yet a likelihood ratio test cannot accept joint insignificancy of the coefficients, except for the constant terms, at the one percent significance level.

The parameter κ corresponding to the inclusive value is -.8977 and hence outside the (0,1) range. It is inaccurately measured with a 95 percent interval of (-3.812, 5.210). Neither the sequential nor the multinomial logit model can be rejected at the usual significance levels.

In the next step of the empirical analysis, the determinants of innovation expenditures are investigated. A main issue in this analysis is the question whether or not innovation cooperation increases innovation expenditures. Since cooperation choice is likely to be endogenous to innovation effort, a simultaneous model for both decisions is estimated. This model is discussed in Appendix D.

The estimation starts with a binary probit model for the decision whether or not to cooperate as a first step. In a second step, an OLS model is estimated where the fitted values of the first–step estimates are included as Heckman–type correction terms. The estimates obtained from the OLS estimation are consistent, their variance–covariance matrix is, however, inconsistent if the Heckman–type correction terms are significantly different from zero.

The binary probit estimation contains the same variables as in the nesting logit approach presented earlier. Since the results of the probit estimation for cooperation choice do not differ qualitatively from those already presented in Table 1, estimation results of the probit equation are not displayed here.

It has to be stressed that misspecification of the first–stage–model of course has severe consequences on the second–stage–estimates. I therefore calculated simulated residuals along the lines of Gourieroux et al. (1987). Diagnostic plots of the simulated residuals against the individual variables included in the estimation and against the fitted latent variable did not indicate evidence for heteroscedasticity.[20] Further, normality of the simulated residuals could not be rejected at the usual significance levels.[21]

Instead of modeling innovation expenditures in absolute term, I scale innovation expenditures by the number of employees in order to control for firm size effects. I take the natural logarithm of this innovation intensity so that the coefficients related to the spillovers pools and to the firms size variables represent elasticities. The coefficients corresponding to the other variables represent growth rates.

The specification of innovation intensity includes the variables already contained in the first stage estimation, and the diversification index $DIVERS$ and the $SALES$–dummy variables. Estimation results are displayed in Table 2.

A first striking results is that coefficients corresponding to the Heckman–type correction terms, $\rho\sigma_u D\hat{\mu}$ and $\rho\sigma_u(D-1)\hat{\lambda}$, are neither independently nor jointly (p–value .618) significantly different from zero so that the variance–covariance matrix of the two–step

[20] I also found that the correlations between the residuals and the explanatory variable (both linear and squared) are below .04 in absolute value.

[21] A joint test for skewness and kurtosis as suggested by D'Agostino et al. (1990) and as implemented in the STATA6.0 option `sktest` was performed here.

procedure is consistently estimated.

The estimation results indicate a significantly positive impact of horizontal spillovers on innovation intensity. The impact of vertical spillovers is insignificant and positive. The spillover pool variables are jointly significant at the ten percent significance level. Innovation productivity as measured by the variable $SCIENCE$ is insignificant and positive. In line with my theoretical model, an increase in market demand, as proxied by export share EXS, leads to an increase in innovation effort. The effect is significant at the one percent significance level.

The effects of the control variables for observable firm heterogeneity can be summarized as follows (only significant coefficients are considered): innovation intensity of East German firms is 24.8 percent lower than that of West German firms. The effect of firm size on innovation intensity is U–shaped. Innovation intensity decreases with firm size over the within–sample firm–size range. The sector affiliation dummy variables turn out to be jointly significant. Business–related services firms invest significantly more in innovation per capita than firms from trade and 'other' services. There is no significant difference between 'other' services and trade in this respect. The coefficient related to the diversification index is positive and highly significant indicating that firms more diversified firms invest more in innovation than less diversified firms. The dummy variables denoting past sales changes are jointly significant. Their sign indicate a nonlinear relationship between past sales changes and current innovation efforts.

Last, the effect of innovation cooperation on innovation effort is analyzed. The estimation results imply a decrease in innovation intensity of 20 percent if a RJV is started. The related standard error is 5.13 percent. With respect to the theoretical model, condition (13) which denotes the condition under which innovation effort under RJV is larger than under innovation competition, is satisfied empirically.

By inclusion of the cooperation dummy term as shown in Table 2, it is assumed that the difference between innovation intensities of cooperating and non–cooperating firms can be completely captured by the dummy variable $COOP$. By recalling from equations (10) and (12) that the effects of spillover, substitution elasticity, market demand and the generality of the R&D approach may differ between cooperating and non–cooperating firms, it seems likely that a shift parameter such as a cooperation dummy variable is not sufficient to capture differences in the innovation intensity of cooperating and non–cooperating firms. Therefore, I have run Minimum Distance Estimations to test whether there are significant differences in the determinants of innovation intensity of cooperating and non–cooperating firms. The MDE is explained in Appendix E. Table 3 displays estimation results for cooperating and non–cooperating firms as well as the corresponding MDE. In order to control for endogenous sample switch, I have enclosed Heckman (1979) correction terms which were calculated on the basis of the first–stage probit estimates of the simultaneous model. These terms turned out to be insignificantly different from zero so that they were left out in the final specification shown in Table 3.

By and large, the estimation results differ only very slightly across cooperating and non–cooperating firms. Indeed, a test for identity of the two parameters vectors cannot reject that the parameter vector for cooperating and non–cooperating firms are identical. Significant different coefficients of both parameter vectors are those related to (i) horizontal spillovers (significantly different at the 3 percent marginal significant level) and (ii) market demand (significantly different at the 5 percent marginal significant level). Both effects are larger for cooperating firms than for non–cooperating firms. Since there are only slight qualitative differences between the results displayed in Table 3 and those shown in Table 2, a further discussion of the estimation results can be omitted here.

Comparing the empirical findings with the predictions of the theoretical model as summarized in section 2.6 we find that:

(1) As expected from the theoretical model, cooperations are more often found between vertically rather than between horizontally related firms.

(2) Spillovers are not large enough to satisfy condition (13) from the theoretical model. Innovation efforts under RJV are smaller than those under Cournot competition.

(3) An increase in market demand leads to an increase in innovation intensity as predicted by the theoretical model.

(4) As predicted by the theoretical model, the more general the R&D approach is, the more is spent on innovation.

(5) The effects of horizontal and vertical spillovers on research efforts are positive and jointly significant.

(6) The disincentive effect of spillovers on RJV formation is not supported by the empirical evidence. The estimates show an insignificant effect of spillovers on RJV formation.

(7) In accordance with the theoretical model, m ore general R&D approaches lead to an increased likelihood of RJV formation.

(8) An increase in market demand has a positive but insignificant impact on RJV formation. The theoretical model predicts a positive effect.

5 Conclusion

This paper presents a three–stages Cournot duopoly game for R&D cooperation, R&D expenditure and product market competition. In this model, the amount of knowledge of firm j freely available to firm j, e.g., the amount of spillovers, is made dependent on firm j's own innovation effort with firm j's absorptive capacity increasing in own innovation effort.

Main results derived from the theoretical model are that if spilovers are sufficiently large, R&D investment is larger under RJV than under R&D competition. Increasing market demand leads to increasing R&D expenditures both under RJV and Cournot competition. For sufficiently general R&D approaches, this is also true for R&D approaches becoming more general. More general R&D approaches also lead to an increased likelihood of RJV formation. Likewise, increased market demand creates incentives to form a RJV.

In the empirical part of this paper, the implications of the theoretical model are tested using innovation survey data. While existing analysis are restricted to manufacturing industries, this study provides evidence for the service sector. A main finding of the empirical analysis is that innovation effort under RJV is 20 percent smaller than under competition with a standard error of 5.13 percent. Consistent with the theoretical model, it is shown that an increase in market demand leads to an increase in innovation effort. The effect of spillovers on innovation expenditures is positive. In accordance to the theoretical model, the impact of spillovers on RJV formation also is positive. The effect, however, is insignificant. The generality of the R&D approach has a significant and positive effect on innovation spending.

Summarizing, the empirical findings are broadly consistent with the theoretical model. Further research will be devoted to move the theoretical model closer to reality. Therefore, my future innovation efforts will focus on extending the model to an oligopoly game and to allow the model to capture product innovation. A second straightforward extension is the explicit modeling of the choice between horizontal and vertical cooperation. On the empirical side, it seems worthwhile to consider the impact of alternative cooperation modes on innovation intensity. In this paper, the simultaneous model of research collaboration and research effort does not distinguish between horizontal and vertical cooperation.

Table 1

Nesting logit estimation results for cooperation choice

	P(no cooperation)			P(mixed cooperation)		
	base: P(cooperation)			base: P(vert. cooperation)		
	Coeff.	Std. err.	marg. eff. (%)	Coeff.	Std. err.	marg. eff. (%)
$ln(S^h)$	-0.1558	0.2093	-2.330	-0.1324	0.1405	-2.295
$ln(S^v)$	-0.7431	1.6074	-4.336	0.6990	2.2556	18.395
$PRIVATE$	-0.4751	1.0953	-7.672	-0.5149	1.1271	-11.813
$SCIENCE$	-2.1260***	0.6789	-23.228	-0.1245	0.9143	-2.099
EXS	-0.1577	0.9141	-5.321	-0.7155	0.8600	-16.806
$EAST$	0.0666	0.7087	3.047	0.4592	0.3800	12.428
$LSIZE$	-0.1856	0.4296	-0.598	0.2697	0.4721	7.711
$LSIZE^2$	0.0046	0.0475	-0.115	-0.0322	0.0481	0.199
$TRANS$	-2.0739	1.0731		-0.5394	1.0320	
BRS	-1.1490**	1.6321		-1.0943*	0.7585	
$CONSTANT$	14.9532*	9.1943		-2.3641	15.1760	
κ	-0.8977	2.8402				
# of obs.	1,212					
McFadden R^2	.056					

***, **, *, significant at the 1, 5 and 10 percent significance level, respectively.

Marginal effects are presented for the continuous variables only.

The number of observations is 1,212, the McFaden pseudo R^2 is .056.

Table 2

Simultaneous model for cooperation and innovation intensity

	Coeff.	Std. err.
$ln(S^h)$	0.1226***	0.0430
$ln(S^v)$	0.4993	0.4804
$PRIVATE$	-0.5045**	0.2697
$SCIENCE$	0.7115**	0.3686
EXS	0.5080**	0.2463
$EAST$	-0.2295***	0.0955
$TRADE$	0.8675**	0.4227
BRS	0.1259	0.3348
$LSIZE$	-0.3105**	0.1110
$LSIZE^2$	0.0071	0.0116
$DIVERS$	0.3528***	0.0758
$SALES--$	-0.2209	0.1901
$SALES-$	0.0565	0.1294
$SALES+$	-0.0748	0.1093
$SALES++$	0.0492	0.1350
$CONSTANT$	-8.3812**	3.9452
D	-0.4012	1.2762
$\rho\sigma_u\hat{\mu}D$	0.3008	0.6531
$\rho\sigma_u\hat{\lambda}(D-1)$	0.3938	1.2042
# of obs.	1,212	
adj. R^2	.1482	

***, ** significant at the 1 and 5 percent significance level, respectively.

The terms $\hat{\mu}$ and $\hat{\lambda}$ denote the Heckman–type correction terms as described in Appendix D.

Table 3

Parameter estimates for the determinants of innovation intensity for cooperating and non–cooperating firms as well as the corresponding Minimum Distance Estimates

	cooperation		MDE		no cooperation	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
$ln(S^h)$	0.2087***	0.0906	0.1023***	0.0250	0.1001***	0.0250
$ln(S^v)$	-1.7968*	1.3940	0.7413*	0.4987	0.8125**	0.4997
$PRIVATE$	-0.4944	0.6365	0.5207**	0.2431	-0.4975**	0.2448
$SCIENCE$	0.7132*	0.5267	0.5831***	0.1983	0.5591***	0.1994
EXS	1.0956**	0.6291	0.3896**	0.2365	0.3594	0.2373
$EAST$	-0.3128	0.2736	0.2043***	0.0901	-0.2026***	0.0903
$TRADE$	1.1387**	0.6375	0.7167***	0.1815	0.7052***	0.1819
BRS	0.2000	0.4946	0.0258	0.1455	0.0244	0.1461
$LSIZE$	-0.5341***	0.2343	0.2782***	0.1188	-0.2540**	0.1231
$LSIZE^2$	0.0202	0.0211	0.0037	0.0123	0.0012	0.0128
$DIVERS$	0.2825*	0.2177	0.3582***	0.0835	0.3556***	0.0838
$SALES--$	-0.4760	0.5553	0.2317	0.1904	-0.2470	0.1908
$SALES-$	-0.4126	0.3839	0.1063	0.1445	0.1114	0.1449
$SALES+$	0.0028	0.3338	0.0957	0.1154	-0.1036	0.1157
$SALES++$	0.0621	0.3992	0.0283	0.1452	0.0162	0.1456
$CONSTANT$	7.2825	9.5999	9.6338***	3.3381	10.1423***	3.3461
# of obs.	165		1,212		1,047	
adj. R^2	.2337		.1310		.1363	

***, **, * significant at the 1, 5 and 10 percent significance level, respectively.

Appendix A: Linear combinations for canonical correlation

private information sources		
customers	0.3264***	0.0668
suppliers	0.4518***	0.0544
competitors	0.3684***	0.0588
scientific information sources		
universities	0.1184*	0.0756
public research inst.	0.3292***	0.0965
fares, exhibitions	0.6301***	0.0631
patent system	0.0832	0.0680

***, * significant at the 1 and 10 percent significance level, respectively.

The canonical correlations are 0.3673, 0.1033 and 0.0354, respectively. The number of observations is 1,284.

Appendix B: Descriptive statistics

	Mean/ share	Std. err.
$ln(innovation\ intensity)$	-5.2285	1.5107
$ln(S^h)$	0.6730	2.2511
$ln(S^v)$	6.4950	0.0962
$PRIVATE$	3.0154	0.2532
$SCIENCE$	2.6637	0.2854
EXS	0.0581	0.1847
$EAST$	0.3721	0.4836
$TRADE$	0.2970	0.4571
BRS	0.5231	0.4997
$LSIZE$	4.1900	1.7070
$LSIZE^2$	20.4678	16.8064
$DIVERS$	1.5486	0.5292
$SALES--$	0.0668	0.2498
$SALES-$	0.1601	0.3668
$SALES+$	0.4101	0.4920
$SALES++$	0.1526	0.3598

Appendix C: The van Ophem and Schram estimator

The indirect utilities $y^*_{d,i}$ of the choices 'cooperation' ($coop$), 'no cooperation' ($no\ coop$), 'vertical cooperation' ($vert$), and 'mixed cooperation' (mix) for firm i ($d = coop, no\,coop, vert, mix$) are assumed to be linear and dependent on a set of explanatory variables summarized in row vector $\boldsymbol{x_t}$:

$$\begin{array}{lclclcl} y^*_{coop,i} & = & \boldsymbol{x_t\vartheta} & + & \lambda\kappa\ I_i & + & \omega_{no\ coop,i}, \\ y^*_{no\ coop,i} & = & \boldsymbol{x_t\tau} & & & + & \omega_{coop,i}, \\ y^*_{vert(coop),i} & = & \boldsymbol{x_t\alpha} & & & + & \omega_{vert(coop),i}, \\ y^*_{mix(coop),i} & = & \boldsymbol{x_t\gamma} & & & + & \omega_{mix(coop),i}, \end{array} \tag{19}$$

where the inclusive value I_i is given by $I_i = log[exp(\boldsymbol{x_t\alpha}) + exp(\boldsymbol{x_t\gamma})]$. The error terms are type I extreme value distributed. Error term $\omega_{no\ coop,i}$ is independent of $\omega_{coop,i}$. Further, $\omega_{no\ coop,i}$, $\omega_{vert(coop),i}$, $\omega_{hori(coop),i}$, and $\omega_{mix(coop),i}$ are independent. Unless $\kappa = 0$, $\omega_{coop,i}$ is correlated with $\omega_{vert(coop),i}$, $\omega_{hori(coop),i}$, and $\omega_{mix(coop),i}$. The indicator variables $y_{d,i}$ take on the value 1 if the dth option is chosen, and 0 otherwise. It follows that

$$\begin{array}{lclcl} P_{coop,i} & = & P[y_{coop,i} = 1] & = & \frac{exp(\boldsymbol{x_t\vartheta}+\kappa I_i)}{exp(\boldsymbol{x_t\tau})+exp(\boldsymbol{x_t\vartheta}+\kappa I_i)} \\ P_{no\ coop,i} & = & P[y_{no\ coop,i} = 1] & = & \frac{exp(\boldsymbol{x_t\tau})}{exp(\boldsymbol{x_t\tau})+exp(\boldsymbol{x_t\vartheta}+\kappa I_i)} \\ P_{vert(coop),i} & = & P[y_{vert} = 1 | y_{coop} = 1] & = & \frac{exp(\boldsymbol{\alpha x_t})}{exp(\boldsymbol{x_t\alpha})+exp(\boldsymbol{x_t\gamma})} \\ P_{mix(coop),i} & = & P[y_{mix} = 1 | y_{coop} = 1] & = & \frac{exp(\boldsymbol{\gamma x_t})}{exp(\boldsymbol{x_t\alpha})+exp(\boldsymbol{x_t\gamma})}. \end{array} \tag{20}$$

In order to achieve identification, the following restrictions are imposed: $\boldsymbol{\alpha}$=0 and $\boldsymbol{\vartheta}$=0.

The loglikelihoodfunction corresponding to firm i is:

$$log\ L_i \ = \sum_{d=coop,no\ coop} y_{d,i}\ P(d)_i \ + \sum_{d=vert,mix} y_{d,i}\ P(d)_i, \tag{21}$$

where the first part of equation (21) corresponds to the choice between cooperation and no cooperation and the second part corresponds to the choice between vertical, horizontal a mixed cooperation, given the firm decided to cooperate at all in the first stage. Equation (21) could be estimated by a two–step procedure which yielded consistent estimates for the coefficients but not for the variance–covariance matrix since the information matrix related to (21) is not block–diagonal. Thus, I estimated the model using a full information maximum likelihood procedure.[22]

The gradients corresponding to equation (21) are given by:

$$\begin{aligned}
\frac{\partial log\ L_i}{\partial \boldsymbol{\tau}} &= \boldsymbol{x_t} \odot (y_{no\ coop,i} - P_{no\ coop,i}) \\
\frac{\partial log\ L_i}{\partial \kappa} &= I_i(y_{coop,i} - P_{coop,i}) \\
\frac{\partial log\ L_i}{\partial \boldsymbol{\gamma}} &= \boldsymbol{x_t} \odot \Big(y_{mix,i}P_{vert,i} + P_{mix,i}(\kappa(y_{coop,i} - P_{coop,i}) - y_{vert,i})\Big).
\end{aligned} \tag{22}$$

The marginal effects corresponding to the probabilities shown in equations (20) are:

$$\begin{aligned}
\frac{\partial P_{coop,i}}{\partial \boldsymbol{x_t}} &= -\Big(P_{coop,i}\ P_{no\ coop,i}\ P_{vert,i}\Big) \odot \Big(\boldsymbol{\tau} + exp(\boldsymbol{x_t}\boldsymbol{\gamma}) \odot (\boldsymbol{\tau} - \boldsymbol{\gamma}\kappa)\Big) \\
\frac{\partial P_{no\ coop,i}}{\partial \boldsymbol{x_t}} &= -\frac{\partial P_{coop,i}}{\partial \boldsymbol{x_t}}, \\
\frac{\partial P_{vert,i}}{\partial \boldsymbol{x_t}} &= -(P_{vert,i}\ P_{mix,i}) \odot \boldsymbol{\gamma} \\
\frac{\partial P_{mix,i}}{\partial \boldsymbol{x_t}} &= -\ \frac{\partial P_{vert,i}}{\partial \boldsymbol{x_t}}.
\end{aligned} \tag{23}$$

[22]The estimation of the van Ophem and Schram [1997] procedure as well as the Minimum Distance Estimation were performed using our own GAUSS program based on the MAXLIK application module. A copy of the programs can be obtained from the author upon request. Analytical gradients were provided in both cases.

Appendix D: The simultaneous equations model

The theoretical model derived in section 2 of this paper implies that R&D cooperation is endogenous for R&D intensity. Hence, a simultaneous model for R&D cooperation and R&D intensity is also needed to test if R&D intensity is larger under R&D cooperation than under R&D competition.

Let D_i denote firm i's cooperation decision. D_i takes on the value 1 if firm i is involved in a R&D cooperation, and 0 otherwise. Firm i is assumed to be engaged in a R&D cooperation if the latent variable D_i^* larger than zero:

$$D_i \;=\; \begin{cases} 1 \quad \text{if} \quad D_i^* \;=\; \boldsymbol{Z_i}\,\boldsymbol{d} \;+\; v_i \;>\; 0 \\ 0 \quad \text{otherwise,} \end{cases} \tag{24}$$

where $\boldsymbol{d}$ is a vector of parameters relating the vector of explanatory variables $\boldsymbol{Z_i}$ to D_i^*. R&D intensity, henceforth denoted by $R\&D$, is given by a linear relation between a set of explanatory variables summarized in vector $\boldsymbol{X_i}$ and the dummy variable for the R&D cooperation decision:

$$R\&D_i \;=\; \boldsymbol{X_i b} \;+\; cD_i \;+\; u_i, \tag{25}$$

where $\boldsymbol{X_i}$ and c relate $\boldsymbol{X_i}$ and D_i to $R\&D_i$, respectively. The disturbance terms v_i and u_i are bivariate i.i.d. normal distributed with mean zero and variance–covariance $\boldsymbol{\Sigma}$. Note that

$$E[u_i \mid -(v_i + \boldsymbol{Z_i d}) > 0] \;=\; -\;\rho\,\sigma_u\,\frac{\phi(-\frac{\boldsymbol{Z_i d}}{\sigma_v})}{\Phi(\frac{-\boldsymbol{Z_i d}}{\sigma_v})} \;=\; -\,\rho\,\sigma_u\,\hat{\lambda}_i, \tag{26}$$

where σ_u and σ_v are the standard errors of the disturbance terms u and v, respectively, and that

$$E[u_i| - (v_i + \boldsymbol{Z_i d}) < 0] \;=\; \rho\,\sigma_u\,\frac{\phi(\frac{\boldsymbol{Z_i d}}{\sigma_v})}{\Phi(\frac{\boldsymbol{Z_i d}}{\sigma_v})} \;=\; \rho\,\sigma_u\,\hat{\mu}_i. \tag{27}$$

The R&D intensity equation accounting for endogeneity of the cooperation decision is

$$R\&D_i \;=\; \boldsymbol{X_i b} \;+\; cD_i \;+\; \rho\sigma_u\hat{\mu}_i D_i \;-\; \rho\sigma_u\hat{\lambda}_i(1-D_i) \;+\; v_i. \tag{28}$$

Equation (28) can be estimated in a two–step procedure. First, estimate $\boldsymbol{d}/\sigma_v$ by a probit model and calculate $\hat{\lambda}_i$ and $\hat{\mu}_i$. Second, estimate equation (28) by OLS. This procedure leads to consistent to consistent parameter estimates. The related variance–covariance matrix, however, is inconsistently estimated. Therefore, I estimate the equation system using a full information maximum likelihood approach.

Abbreviating $u_i + \boldsymbol{X_i b} + c = z_i$, the conditional density of $R\&D_i$, conditional on R&D cooperation ($D_i = 1$), is is equal to the density of $z \mid D = 1$: $f(R\&D_i \mid v_i > -\boldsymbol{Z_i d}) \;=\; f(z_i \mid v_i > -\boldsymbol{Z_i d})$. Likewise, $f(R\&D_i \mid v_i < -\boldsymbol{Z_i d}) \;=\; f(z_i \mid v_i < -\boldsymbol{Z_i d})$. z_i and v are bivariate normal distributed:

$$\begin{pmatrix} z_i \\ \\ v_i \end{pmatrix} \;=\; N\left(\begin{pmatrix} \boldsymbol{X_i b} + c \\ \\ 0 \end{pmatrix},\; \Sigma\right). \tag{29}$$

It then follows that

$$f(z_i \mid v > -\boldsymbol{Z_i d}) \;=\; \frac{\phi(z)}{\Phi(\frac{-\boldsymbol{Z_i d}}{\sigma_v})}\;(1 - \Phi(\frac{-\boldsymbol{Z_i d} - \frac{\sigma_{uv}}{\sigma_u^2}(z_i - \boldsymbol{X_i b} - c)}{\sigma_v\sqrt{1-\rho^2}})) \tag{30}$$

and that

$$f(z_i \mid v < -\boldsymbol{Z_i d}) \;=\; \frac{\phi(z)}{\Phi(\frac{\boldsymbol{Z_i d}}{\sigma_v})}\;\Phi(\frac{-\boldsymbol{Z_i d} - \frac{\sigma_{uv}}{\sigma_u^2}(z_i - \boldsymbol{X_i b} - c)}{\sigma_v\sqrt{1-\rho^2}})) \tag{31}$$

The likelihood function l is then given by

$$l \;=\; \Pi_{D=0}\;\Phi(v < -\boldsymbol{Z_i d})f(z_i \mid v < -\boldsymbol{Z_i d})\;\Pi_{D=1}\;\Phi(v > -\boldsymbol{Z_i d})f(z_i \mid v > -\boldsymbol{Z_i d}). \tag{32}$$

Appendix E: The Minimum Distance Estimator

In order to test if there is a common structure in the parameter estimates for the choice of the alternative vertical information sources, a Minimum Distance Estimator (MDE) is used. A thorough discussion of the MDE an applications are presented in Kodde et al. (1990). Minimum Distance Estimation involves the estimation of the M reduced form parameter vectors in a first stage. In the present case, these reduced form parameters are the parameter estimates obtained from running separate tobit regressions for the choice alternative cooperation modes. In the second stage, the Minimum Distance Estimator is derived from minimizing the weighted difference between the auxiliary parameter vectors obtained in the first stage.

Besides the practical advantage that the MDE can be easily implemented empirically, it has the further benefit that it provides the researcher with a formal test of common structures among the auxiliary parameter vectors. The MDE is derived from minimizing the distance between the auxiliary parameter vectors under the following set of restrictions:

$$f(\boldsymbol{\beta}, \hat{\boldsymbol{\theta}}) \;=\; \boldsymbol{H}\;\boldsymbol{\beta} \;-\; \hat{\boldsymbol{\theta}} \;=\; \mathbf{0}, \tag{33}$$

where the $M \cdot K \;\times\; K$ matrix $\boldsymbol{H}$ imposes $M \cdot K$ restrictions on $\boldsymbol{\theta}$. The $M \cdot K \times 1$ vector $\hat{\boldsymbol{\theta}}$ contains the M stacked auxiliary parameter vectors. In the present case, $\boldsymbol{H}$ is defined by $M \quad K \times K$–dimensional stacked identity matrices. The MDE is given by the minimization of:

$$D(\boldsymbol{\beta}) \;=\; f(\boldsymbol{\beta}, \hat{\boldsymbol{\theta}})' \; \hat{V}[\hat{\boldsymbol{\theta}}]^{-1} \; f(\boldsymbol{\beta}, \hat{\boldsymbol{\theta}}), \tag{34}$$

where $\hat{V}[\hat{\boldsymbol{\theta}}]$ denotes the common estimated variance–covariance matrix of the auxiliary parameter vectors. Minimization of D leads to

$$\hat{\boldsymbol{b}} \;=\; (H' \, \hat{V}[\hat{\boldsymbol{\theta}}]^{-1} \; H)^{-1} H' \, \hat{V}[\hat{\boldsymbol{\theta}}]^{-1} \; \hat{\boldsymbol{\theta}} \tag{35}$$

with variance–covariance matrix

$$\hat{V}[\hat{\boldsymbol{b}}] \;=\; \Big(H' \, \hat{V}[\hat{\boldsymbol{\theta}}]^{-1} \; H\Big)^{-1}. \tag{36}$$

In the present case, where the three equations were estimated using different samples, $V[\hat{\boldsymbol{\theta}}]$ is a matrix carrying the estimated variance–covariance matrices of the first stage parameter vectors on its diagonal blocks. The off–diagonal blocks of $V[\hat{\boldsymbol{\theta}}]$ are given by the matrix $\sigma_{ST} \; (\boldsymbol{X'X})^{-1}$ with $\sigma_{st} = 1/N \; \hat{\boldsymbol{\epsilon}}_{\boldsymbol{s}} \hat{\boldsymbol{\epsilon}}_{\boldsymbol{t}}$ and N denoting the number of observations and $\boldsymbol{X}$ denoting the matrix of explanatory variables. The subscripts s and t correspond to the auxiliary first stage regressions.

For testing the null hypotheses that the M auxiliary parameter vectors coincide with one another, the following Wald–type test statistics can be applied:

$$f(\boldsymbol{\beta}, \hat{\boldsymbol{\theta}})' \; \hat{V}[\hat{\boldsymbol{\theta}}]^{-1} \; f(\boldsymbol{\beta}, \hat{\boldsymbol{\theta}}) \;\sim\; \chi^2_{(M-1)\cdot K} \;\; . \tag{37}$$

References

Aldrich, J.H. and F.D. Nelson, 1989, Linear probability, logit, and probit models (Sage University Press, Beverly Hills).

Arundel, A. and I. Kabla, 1998, What Percentage of Innovations are Patented? Empirical Estimates for European Firms. Research Policy 27 (2), 127–141.

Beaudreau, B., 1996, R&D: To compete or to cooperate?, Economics of Innovation and New Technology 4, 173–186.

Beath, J., Y. Katsoulacos and D. Ulph, 1988, R&D rivalry vs. R&D cooperation under uncertainty, Recherches Economiques de Louvain 54, 373–384.

Beath, J., Y. Katsoulacos and D. Ulph, 1997, Sequential product innovation and industry evolution, The Economic Journal 97, 32–43.

Beath, J., J. Poyago–Theotoky, and D. Ulph, 1998, Organization design and information–sharing in a research joint venture with spillovers, Bulletin of Economic Research 50 (1), 47–59.

Beath, J., and D. Ulph, 1992, Game–theoretic approaches, in: P. Stoneman, ed., Handbook of the economics of innovation and technical change (Blackwell publishers, Oxford).

Blundell, R., F. Laisney and M. Lechner, 1993, Alternative interpretations of hours information in an econometric model of labour supply, Empirical Economics 18, 393–415.

Brander, J.A. and B. Spencer, 1984, Strategic commitment with R&D: the symmetric case, Bell Journal of Economics 14, 225–235.

Branstetter, L., 1998, Looking for international knowledge spillovers: A review of the literature with suggestions for new approaches, Annales D'Économie et de Statistique 49/50, 517–540.

Brouwer, E., Kleinknecht, A., 1999. Innovative Output, and a Firm's Propensity to Patent. An Exploration Using CIS Micro Data. Research Policy 28 (6), 615–624.

Choi, J. P., 1993, Cooperative R&D with product market competition, International Journal of Industrial Organisation 11, 553-571.

Cohen, W.M., 1995, Empirical studies of innovative activity, in: P. Stoneman, ed., Handbook of the economics of innovation and technical change (Blackwell publishers, Oxford).

Cohen, W.M. and D.A. Levinthal, 1989, Innovation and Learning: The Two Faces of R&D, The Economic Journal 99, 569–596.

Cohen, W.M. and D.A. Levinthal, 1990, Absorptive capacity: a new perspective on learning and innovation, Administrative Science Quarterly 35, 128–152.

D'Agostino, R.B., A. Balanger and R.B. D'Agostino, Jr., 1990, A suggestion for using powerful and informative tests for normality, The American Statistician 44, 316–321.

D'Aspremont, C. and A. Jacquemin, 1988, Cooperative and noncooperative R&D in duopoly with spillovers, The American Economic Review 75, 1133-1137.

D'Aspremont, C. and A. Jacquemin, 1990, Cooperative and noncooperative R&D in duopoly with spillovers: Erratum, The American Economic Review 80, 641-642.

DeBondt, R., 1996, Spillovers and innovative activities, International Journal of Industrial Organization 15, 1–28.

DeBondt, R., and K. Kesteloot, 1993, Demand–creating R&D in a symmetric oligopoly, Economics of Innovation and New Technlogy 2, 171–183.

DeBondt, R., P. Slaets and B. Cassiman, 1992, Spilovers and the number of rivals for maximum effective R&D, International Journal of Industrial Organization 10, 35–54.

DeBondt, R., and R. Veugelers, 1991, Strategic investment with spillovers, European Journal of Political Economy 7, 345–366.

Deneckere, R. and C. Davidson, 1985, Incentives to form coalitions with Bertrand competition, Rand Journal of Economics 16, 473–486.

Eymann, A., 1995, Consumers' spatial choice behaviour (Physica–Verlag, Heidelberg).

Fölster, S., 1995, Do subsidies to cooperative R&D actually stimulate R&D investment and cooperation?, Research Policy 24, 403-417.

Geroski, P., 1993, Antitrust policy towards co–operative R&D ventures, Oxford Review of Economic Policy 9, 58–71.

Geroski, P., 1995, Do spillovers undermine the incentives to innovate? in: S. Dowrick, ed., Economic approaches to innovation (Ashgate, Brookfield).

Gersbach, H. and A. Schmutzler, 1999, Endogenous spillovers and incentives to innovate, working paper socioeconomic institute University of Zurich.

Gourieroux C., A. Monfort, E. Renault and A. Trognon, 1987, Simulated residuals, Journal of Econometrics 34, 201–252.

Griliches, Z., 1990, Patent statistics as economic indicators: a survey, Journal of Economic Literature 28, 1661–1707.

Harhoff, D., 1999, Strategic spillovers and incentives for research and development, Management Science 42, 907–925.

Inkmann, J., 1999, Horizontal and vertical R&D cooperation. University of Konstanz discussion paper.

Irwin, D. A. and P. J. Klenow, 1996, High-tech R&D subsidies. Estimating the effects of Sematech, Journal of International Economics 40, 323–344.

Jaffe, A.B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value, The American Economic Review 76, 584–1001.

Jaffe, A.B., 1988. Demand and supply influences in R&D intensity and productivity growth, The Review of Economics and Statistics 70, 431–437.

Janz, N. and G. Licht, ed., 1999, Innovationsaktivitäten der deutschen Wirtschaft (Nomos–Verlag, Baden–Baden).

Jorde, T.M. and D.J. Teece, 1990, Innovation and cooperation: implications for antitrust, Journal of Economic Perspectives 4, 75–96.

Kaiser, U., 1999, Measuring knowledge spillovers in manufacturing and services: an empirical assessment of alternative approaches, ZEW discussion paper 99–62.

Kaiser, U. and G. Licht, 1998, R&D cooperation and R&D intensity: theory and micro–econometric evidence for German manufacturing industries, ZEW discussion paper 98–26.

Kamien, M. I., E. Muller and I. Zang, 1992, Research joint ventures and R&D cartels, American Economic Review 82, 1293-1306.

Kamien, M. I. and I. Zang, I., 1998, Meet me halfway: research joint ventures and absorptive capacity, paper presented at the EARIE conference 1998 at Copenhagen.

Katsoulacos, Y. and D. Ulph, 1998a, Endogenous spillovers and the performance of research joint ventures, Journal of Industrial Economics 46, 333-357.

Katsoulacos, Y. and D. Ulph, 1998b, Innovation spillovers and technology policy, Annales D'Économie et de Statistique 49/50, 589–607.

Katz, M., 1986, An analysis of cooperative research and development, Rand Journal of Economics 17, 527–543.

König, H., G. Licht and M. Staat, 1994, F&E–Kooperationen und Innovationsaktivität, in: B. Gahlen, H.J. Ramser and H. Hesse, eds., Ökonomische Probleme der europäischen Integration, Schriftenreihe des wirtschaftswissenschaftlichen Seminars Ottobeuren 23 (Mohr, Tübingen).

Kodde, D.A., F.C. Palm, and G.A. Pfann, 1990, Asymptotic least squares estimation efficiency considerations and applications, Journal of Applied Econometrics, 229–243.

Kogut, B., 1989, The stability of joint ventures: reciprocity and competitive rivalry, The Journal of Industrial Economics 38, 183–198.

Levin, R.C., 1988, Appropriability, R&D spending, and technological performance, The American Economic Review, 424–428.

Levin, R.C., A.K. Klevorick, R.R. Nelson, and S.G. Winter, 1987, Appropriating the returns from industrial research and development, Brookings Papers on Economic Activity 3, 783–820.

Levin, R.C. and P.C. Reiss, 1988, Cost–reducing and demand–creating R&D with spillovers, RAND Journal of Economics 19, 538–556.

Licht, G., C. Hipp, M. Kukuk, and G. Münt, 1997, Innovationen im Dienstleistungssektor (Nomos–Verlag, Baden–Baden).

Mamuneas, T. P., 1999, Spillovers from publicly financed R&D capital in high–tech industries, International Journal of Industrial Organization 17, 215–239.

McFadden, D., 1974, Analysis of qualitative choice behaviour, in: P. Zarembka, Frontiers in econometrics (Academic Press, New York).

Miwa, Y., 1996, Firms and industrial organization in Japan (New York University Press, New York).

Motta, M., 1992, Cooperative R&D and vertical product differentiation, International Journal of Industrial Organization 10, 643–661.

OECD, 1994, OECD proposed guidelines for collecting and interpreting technological innovation data *OSLO Manual* (OECD, Paris).

Pavitt, K., 1985, Patent statistics as indicators of innovative activities: possibilities and problems. Scientometrics 7, 77–99.

Pavitt, K., 1988, Uses and abuses of international patent statistics, in: A.F.J. Van Raen, ed., Handbook of Quantitative Studies of Science and Technology (North Holland, Amsterdam).

Peters, J., 1995, Inter–industry R&D spillovers between vertically related industries: incentives, strategic aspects and consequences, University of Augsburg discussion paper.

Peters, J., 1997, Strategic generation of inter–industry R&D spillovers, paper presented at the European Economic Association annual conference at Toulouse.

Poyago–Theotoky, J., 1995, Equilibrium and optimal size of a research joint venture in an oligopoly with spillovers, The Journal of Industrial Economics, 209–226.

Miwa, Y., 1996, Firms and industrial organization in Japan (New York University Press, New York).

Pudney, S., 1989, Modeling individual choice: the econometrics of corners, kinks and holes (Blackwell, Cambridge).

Röller, L.–H., M.M. Tombak, and R. Siebert, 1998, The incentives to form research joint ventures: theory and evidence, Wissenschaftszentrum Berlin discussion paper FS IV 98–15.

Salant, S.W., and G. Shaffer, 1998, Optimal asymmetric strategies in research joint ventures, International Journal of Industrial Organization 16, 195–208.

Scherer, F.M., 1982, Interindustry technology flows and productivity growth, The Review of Economics and Statistics 64, 627–634.

Scherer, F.M., 1984. Using linked patent and R&D data to measure interindustry technology flows, in Z. Griliches, ed., R&D, patents and productivity (University of Chicago Press, Chicago).

Spence, M., 1984. Cost Reduction, competition, and industry performance, Econometrica 52, 368–402.

Spencer, W. J. and P. Grindley, 1993, SEMATECH after five years: high–technology consortia and U.S. Competitiveness, California Management Review 35, pp. 9-32.

Sutton, J., 1997, Technology and market structure. Theory and history(MIT Press, Cambridge).

Suzumura, K., 1992, Cooperative and noncooperative R&D in an oligopoly with spillovers, American Economic Review 82, 1307-1320.

Tsuru, S., 1993, Japan's capitalism: Creative defeat and beyond (Cambridge University Press, Cambridge).

van Ophem, H. and A. Schram, 1997, Sequential and multinomial Logit: A nested Model, Empirical Economics 22, 131–152.

Vonortas, N.S., 1997, Research joint ventures in the US, Research Policy 26, 577–595.

Ziss, S., 1994, Strategic R&D with spillovers, collusion and welfare, Journal of Industrial Economics 17, 375-393.