Research Cooperation and Research Expenditures with Endogenous Absorptive Capacity
Theory and Microeconometric Evidence for the German Services

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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., firms' absorptive capacity is treated as an endogenous variable. It is shown that cooperating firms invest more in R&D than non–cooperating firms if spillovers are sufficiently large. Further, market demand and R&D productivity have a positive effect on R&D efforts both under research joint venture and under research competition. Firms' propensity to collaborate in R&D is increasing in R&D productivity.
The key findings of the theoretical model are tested using German innovation survey data for the service sector. A simultaneous model for cooperation choice and innovation expenditures shows that R&D cooperation has a weakly significant positive effect on innovation expenditures. The empirical results broadly support the theoretical model.
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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 and to retain market power. 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 German and US research collaborations. Spencer and Grindley (1993) argue that the R&D consortium SEMATECH contributed significantly to the leading position of the US in semiconductor industries. Jorde and Teece (1990) trace the success of German mechanical engineering products in the seventies and eighties back 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 half of all the firms in manufacturing industries conducted cooperative research (König et al., 1994). Based on US Department of Justice data, Vonortas (1997) shows that 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 (1983), Katz (1986) and Spence (1986). A large strand of the more recent literature is built on D'Aspremont and Jacquemin (1988, 1990), who develop a two–stage Cournot duopoly game for R&D expenditures 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; DeBondt et al., 1992; Kamien et al., 1992; Salant and Shaffer (1998), Suzumura, 1992).[2] In a recent contribution, Kaiser and Licht (1998) extend the D'Aspremont and Jacquemin

[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.

[2] A survey of the existing literature can be omitted here since extensive reviews by De Bondt (1996), Cohen (1995) and Geroski (1995) already exist. 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 (1998), on 'The Economics and Econometrics of Innovation' and the references cited therein.

model by accounting for both process and product innovation. They find that the conditions for optimal R&D expenditures have virtually the same structure for both product and process R&D.

A main question in all these papers is: 'Does cooperative R&D increase or decrease R&D efforts?'. The common answer is that it depends on the relation of the level of spillovers to a term usually consisting of product substitutability and market demand. Research spillovers arise whenever knowledge produced by firm i is voluntarily or 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 of research joint venture on research efforts. Due to internalization of spillover — it is assumed that knowledge is fully exchanged in an RJV —, R&D investment is stimulated. Business–stealing counteracts this positive effect on R&D spending and may dominate the positive effect attributable to the internalization of technical spillovers. This is in contrast to the more standard model by Kamien et al. (1992) who show that cooperating firms always invest more in R&D than non–cooperating firms. Their model, however, does not take into account endogeneous absorptive capacity.

Since empirical evidence on the impact of RJVs on R&D investment is scarce, it remains merely an open question in empirical research to determine which effect is predominant. Earlier studies have produced mixed results. Fölster (1995) shows for Sweden that governmental subsidies of R&D cooperations 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 German manufacturing firms. 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 (2000). While at least some empirical evidence exists on the relationship between R&D cooperation and R&D expenditure for manufacturing virtually nothing is known for the service sector. This paper adds to existing empirical studies in that it analyzes the service sector. Although the service sector almost is as innovative as manufacturing industries, empirical evidence on the innovative behavior of the service sector is scarce.[4] Janz and Licht (1999) give a comprehensive comparison between the

[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.

[4] There are, however, a few studies which are concerned with the innovative activity in the service sector: König et al. (1996) study service firms' propensity to engage in co–operative R&D. Kleinknecht (1998) summarizes main findings of a Dutch innovation survey which also comprises the service sector. Kleinknecht and Reijnen (1992) use a related data set to study R&D cooperations in services and manufacturing industries. Gallouj and Weinstein (1997) characterize innovative activity in the services sector. Sirilli and Evangelista (1998) provide empirical evidence on innovative behaviour of Italian service firms. Finally, Amable and Palom-

innovative behaviour of services and manufacturing industries. They find that that 58.4 percent of the firms from the manufacturing sector and 58.8 percent of the firms from the service sector introduced an innovation in 1996. While there are not much differences in these figures, innovation intensity (innovation expenditures scaled by sales) is lower in services than in manufacturing. The innovation intensity in manufacturing is ten percent whereas it is five percent in services. In any case, these figures suggest that innovation plays a major role in the service sector as well so that it is worthwhile to learn more about innovation patterns in this sector.

The theoretical part of this paper shares the essential features of the D'Aspremont and Jacquemin (1988, 1990) model. As in Kamien et al. (1992) and Suzumura (1992), however, the D'Aspremont and Jacquemin 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–stage 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 the extend to which firms can absorb knowledge is assumed to be exogenously determined, it is treated as a function of own innovation efforts this paper. In fact, it appears to be unlikely that firms can gain from each other's knowledge independently of their own research effort. Cohen and Levinthal (1989) have empirically shown and theoretically described that firms' absorptive capacity critically depends on own research efforts. 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.

Important findings of the theoretical model are (1) that cooperations should be more widespread between vertically–related than between horizontally–related firms, (2) that an increase in market demand leads to an increase in R&D efforts and (3) that an increase in R&D productivity positively affects both R&D efforts and RJV formation, (4) that under general conditions an increase in substitutability between products provides disincentives on R&D efforts and (5) that the effect of an increase in the generality of the R&D approach is positive in the R&D effort determination provided that the R&D approach of firms is already sufficiently general. Under the condition that the *direct* effect of changes in market demand, in the elasticity of substitution and in the generality of the R&D approach is larger than the effect of these changes in innovation efforts, the following additional conclusions can be drawn: (1) increasing market demand, (2) increasing generality of the R&D approach provides incentives to form RJVs, and (3) an increase in product substitutability has a negative effect on RJV forma-

barini (1998) conduct a comparison of R&D intensities across agriculture, manufacturing and services for eight OECD countries.

tion.
The main implications of the theoretical model are tested in the empirical part of this paper. Nesting logit models (van Ophem and Schram, 1997) are applied to empirically disentangle the determinants of R&D cooperation.[5] Three modes of cooperation are distinguished: vertical cooperation (cooperation with suppliers or customers), horizontal cooperation (cooperation with competitors) and non–cooperation.
In a further step, the paper aims at uncovering the impact of research cooperation on research expenditures. Since firms may simultaneously decide upon research cooperation and research expenditure, a simultaneous model for the cooperation and the expenditure decision is run.
In a last step, 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 very broadly consistent with the theoretical model. A central result from the empirical investigation is that research collaboration positively and weakly significantly influences innovation intensity.
Other results are that the more general the R&D approach is, the more likely it is that RJVs are formed. R&D productivity also has a U–shaped effect on RJV formation and an inversely U–shaped impact on research expenditures. Positive, although insignificant, effects of both vertical and horizontal spillovers are found for the decision to cooperate. Spillovers, R&D productivity, market demand, and the generality of the R&D approach have a positive and significant impact on innovation expenditures.

2 Theoretical model

2.1 Market demand

In order to keep things tractable and interpretable, this paper deals with process innovation only. 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.[7] The theoretical models of this and the earlier paper

[5] I term it a 'nesting' logit model since the approach of van Ophem and Schram (1997) nests the multinomial, the traditional and the sequential logit model as special cases.

[6] Earlier contributions discussing product innovations are Beath et al. (1997), Bonano and Haworth (1998), Choi (1993), DeBondt and Kesteloot (1993), Levin and Reiss (1988) as well as Motta (1992).

[7] 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 product and process

follow D'Aspremont and Jacquemin (1988, 1990). A theoretical model distinguishing between vertical and horizontal cooperation is presented by Inkmann (2000). Harhoff (1996, 1997) and Peters (1995, 1997) consider strategic investment in R&D which spills over to downstream suppliers. 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).
Models of process R&D are primarily based on systems of linear demand functions. In a duopoly, where two one–product firms compete against one another and produce products q_i and q_j, the utility function of household z to be maximized is assumed to be given by

$$U(q_{iz}, q_{iz}) \;=\; \sum_{i=1}^{2}(q_{iz} - q_{iz}^2) \;-\; 2\sigma q_{iz} q_{jz} \;+\; M_z, \tag{1}$$

where M denotes consumption of an outside good which it is not affected by cross–price effects and which is sold at a price of unity.[8] The budget restriction of household z hence is

$$M_z \;=\; Y_z \;-\; \sum_{i=1}^{2} p_i q_{iz}. \tag{2}$$

The utility function (1) is consistent with the standard utility function used, i.e., by Sutton (1998, ch. 2.8) in a Cournot–framework or by Deneckere and Davidson (1985) in a Bertrand competition context.[9]
The parameter σ is a measure of substitutability of the two goods with $\sigma \in [0, 1]$. If $\sigma = 1$, the two goods are perfect substitutes and if $\sigma = 0$, the extreme case of monopoly is present. Hence, the substitutability parameter σ can also be regarded as a market power parameter. The closer σ is to 0, i.e., the more heterogenous products are, the more market power is retained by the corresponding firm. For $\sigma = 0$ the special case of monopoly power is obtained.
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 total demand for good q_i is given by a linear market demand function:

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

where the quantities q_i and q_j denote market demand instead of individual household demand.

innovation anyway.

[8]However, consumers will adjust M in order to meet the budget constraint if an innovation takes place and product prices of the innovating firm decrease.

[9]The formulation of the utility function (1) departs from the existing literature in that there conventionally appears the coefficient 2 (1/2) before σ (in front of the squared term). Under the normalization chosen here, σ takes values between 0 and 1.

2.2 R&D production function

Following the tradition of R&D cooperation models (c.f. Suzumura, 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, 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.[10]

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 absorptive capacity.

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.[11] 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, 1990; Levin, 1988; Levin et al., 1987, Levin and Reiss, 1988).

The main difference of the model to be outlined here compared to that of Kamien and Zang (1998) is that my model captures a more complex and interesting market demand function since it does not restrict products to be perfect substitutes as in the Kamien and Zang (1998) approach. As it shall turn out later on, the degree of product substitution is an important determinant of R&D expenditures and R&D cooperation.

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 cost function k_i. By conducting R&D, firms can decrease marginal costs. Denoting X_i the *effective* level of R&D — own R&D plus R&D received from other firms — of firm i, the unit cost function of firm i is assumed to be given by:

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

[10] The deterministic R&D model suggested here falls short of real innovation processes which are driven by risk and irreversibilities. Beaudreau (1996) discusses a model that takes into account the uncertainty and multidimensionality without, however, finding markedly different results compared to contributions based on the D'Aspremont and Jacquemin (1988, 1990) framework. My model is also 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.

[11] Other exceptions are the contributions of Katsoulacos and Ulph (1998a and 1998b). In their model, the extent 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.

where $f(X_i)$ denotes the R&D production function of process innovation and c_i denotes fixed costs. The cost function (4) represents per–unit production costs which are measured in monetary units. It is required that

$$f(0) = 0,\ f(X_i) \leq c,\ f'(X_i) > 0,\ f''(X_i) < 0, \qquad (5)$$
$$lim_{X_i \to \infty}\ f'(X_i)\ \to 0 \text{ and } (1 - k_i)f''(X_i) + f'(X_i)^2 < 0.$$

These assumptions assure that no process innovation is achieved if it is not invested in R&D, production costs are positive, the R&D production function is increasing and concave in effective R&D, marginal productivity of R&D goes to zero as effective R&D approaches infinity and that R&D costs show a steeper increase than the returns of R&D so that it is prevented that firms boundlessly invest in R&D. Equation (5) make sure that it is profitable for all firms to conduct R&D.

Following Kamien and Zang (1998), firm i's effective R&D, X_i, depends upon own R&D, x_i and the spillovers firm i receives from other firms. Both effective and own R&D are measured in monetary units. Effective R&D is assumed to be given by

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

with $\delta, \beta \ \in (0, 1)$.[12] Equation (6) implies that if firm i does not invest in R&D at all, it cannot receive any spillovers from other firms' research efforts.

The parameter β denotes the exogenously–given intensity of R&D spillovers. It can, e.g., be interpreted as a parameter reflecting the degree of patent protection. For $\beta = 0$, patents perfectly protect research results, for $\beta = 1$, patents are completely unable to protect research results; β reflects the restricted possibility to protect research results.

The parameter δ denotes firm i's "R&D approach" (Kamien and Zang, 1998, p. 3). That is, if $\delta = 0$, firms are both universal recipients from and universal donors of other firms' R&D efforts ('general R&D approach'). 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 Jacquemin (1988, 1990), DeBondt and Veugelers (1991), Kaiser and Licht (1998), Kamien et al. (1992), Poyago–Theotoky (1995), Röller et al. (1998) and Spence (1984)) for duopolies, $X_i = x_i + \beta x_j$.

At the other extreme, with $\delta = 1$, 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 firms' effective R&D ('specific R&D approach'). If δ lies in between the two extreme cases, effective R&D is homogeneous of degree one in x_i.

Hence, the parameter δ reflects how applied, as opposed to how specific, how

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

oriented towards science, the research program is. For large values of δ, the research program is focused on basic research whereas it aims at applied research for small values of δ. Hence, δ depends on the compatability of the firms' research program.

Effective R&D is increasing and globally concave in both own and the other firm's R&D. If $ln(x_i/x_j) > 1/(1-\delta)$, efficient R&D increases with an increase in the generality of the R&D approach; it decreases if the inequality is reverse. Efficient R&D is globally concave in δ provided that own R&D is larger than the other firm's R&D and globally convex if the reverse is true.

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 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, output is increasing in own R&D effort if a sufficiently specific R&D approach is present: $\delta > \sigma/(2+\sigma)$. If this condition is not met, e.g. the R&D approach is more general, own output increases 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 total spillovers are large, i.e., δ is small and β is large. Under these conditions 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 conduct R&D cooperatively.

The differences to the case of truly exogenous spillovers ($\delta = 0$) as in Kamien et al. (1992) 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 venture should differ with the type of cooperation partner (horizontally related/vertically related partners). E.g., competitive spillovers are smaller in a vertical than in a horizontal cooperation.

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 the 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:

$$max_{x_i}\ \Pi_i \ = \ b\ q_i^*(x_i, x_j)^2 \ - \ x_i, \tag{9}$$

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^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:

$$max_{x_i}\ \Pi_i \ = \ b\ q_i^*(x_i, x_j)^2 \ - \ x_i \ + \ b\ q_j^*(x_i, x_j)^2 \ - \ x_j, \tag{11}$$

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. The optimal R&D equations of Kamien et al. (1992) are obtained by neglecting the endogeneity of absorptive capacity by setting $\delta = 0$. Under RJV — as, e.g. in Beath and Ulph (1992), Kamien et al. (1992), Motta (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

$$\underbrace{f'[X^c](\delta(2+\sigma)-\sigma)(1-k^c)}_{\substack{(+)\\ \textit{technological}\\ \textit{spillover}}} \ + \ \underbrace{x^c(2+\beta(1-\delta)(\delta(2+\sigma)-\sigma)(f'[X^c]^2 + (1-k^c)f[X^c]'')}_{\substack{(-)\\ \textit{competitive}\\ \textit{spillover}}} \ > \ 0 \tag{13}$$

and negative otherwise.[13] This condition simply states that there are two effects working against one another in a RJV: There are positive technological spillovers

[13]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.

which arise from the joint use of research results and there are negative competitive spillovers which is due to the fact that firm i can use firm j's research results to improve its relative competitive position.

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) and using the set of assumptions (5). For sufficiently large spillovers, e.g.,

$$\beta \;\geq\; \frac{(2-\sigma)(2-\delta)-2}{(1-\delta)(\delta(2+\sigma)-\sigma)}, \tag{14}$$

R&D efforts are larger under RJV than under Cournot competition. Condition (14) is always satisfied for specific R&D approaches, $\delta > 2 - \Big(2/(2-\sigma)\Big)$. The difference to the Kamien et al. (1992) special case of truly exogeneous spillovers ($\delta = 0$) are striking since in their model research efforts are always larger under RJV than in research competition.

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,[14] (iii) an increase in market demand leads to an increase in research efforts both under RJV and competition, and (iv) an increase in R&D productivity positively affects research efforts.

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. An RJV is started if:

$$\Pi_i^{jv} \;-\; \Pi_i^c \;=\; b\,\left(q_i^{jv}\right)^2 \;-\; x_i^{jv} \;-\; b\,\left(q_i^c\right)^2 \;+\; x_i^c \;>\; 0. \tag{15}$$

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.

Incentives to start an RJV increase with increasing exogenous spillovers β if $\varepsilon_{x^c,\beta} \;>\; f'[X^c]\;\varepsilon_{x^c,\beta}$ with $\varepsilon_{x^c,\beta}$ denoting the elasticity of research expenditures with respect to spillovers.

It can further be shown that increases in R&D productivity create incentives to form an RJV.

Provided that the *direct* effects of changes in the generality of the R&D approach, in market demand and in product substitutability are larger than their indirect

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

effects via research efforts, it can be shown that increases in the generality of the R&D approach in product substitutability creates disincentive effects to RJV formation and that an increase in market demand creates incentives to form an RJV.

2.6 Testable model implications

The hypotheses derived from the theoretical model can be summarized as follows:

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

(2) An increase in the generality of the R&D approach leads to an increase in R&D investment provided that the R&D approach already is sufficiently general.

(3) An increase in product substitutability leads to a decrease in R&D investment.

(4) An increase in market demand leads to an increase in research efforts.

(5) An increase in research productivity leads to an increase in research efforts.

(6) An increase in research productivity increases the likelihood of RJV formation.

3 Data and empirical implementation

The hypotheses derived from the theoretical model are tested in the empirical part of this paper. A 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 fully replicate the theoretical model. Moreover, the data set used in the empirical analysis does neither contain information on how many cooperations a firm is involved in (just one or more than one) nor on the amount of money spent within an individual RJV.

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 described thoroughly 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: (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 does not ask 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 service firms often do 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. 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 counterpart of exogenous spillovers, β:

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

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. It appears plausible that firms in the same sector manufacture substitutive products while firms from different sectors manufacture complementary products. 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 their own sector. In this study, spillovers from both the service and the manufacturing sector are considered.[15]

Numerous suggestions on how to calculate the spillover parameter ω_{ij} can be found in the literature. 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, I (Kaiser, 1999) review frequently applied methods to proxy ω_{ij} and test them against each other. I find 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 method is due to Jaffe (1986 and 1988), who uses patent citation data to approximate knowledge flows between industries.[16] 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 (cosine) between $\boldsymbol{f_i}$ and $\boldsymbol{f_j}$:

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

If firm i's and firm j's patent activity perfectly coincides, 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' (...)."[17] Although Griliches' remark only matters if the

[15] 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.

[16] 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.

[17] 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.

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.[18]

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 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 general a firm's research approach is, the more heterogenous its

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

information sources are. That is to say that a firm that pursues a general research approach may gain from virtually all available information sources while a firm pursuing a specific research approach may only gain from specific information sources. Fortunately, 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 from the service sector, (2) customers from the producing sector (3) suppliers, (4) competitors, (5) associated firms, (6) management consultancy firms, private research institutions, (7) universities, (8) other public research institutions, (9) fairs and exhibitions, and (10) the patent system. My proxy variable for the generality of research programs is constructed as the number of information sources a firm indicates as 'important' or 'very important'. Three dummy variables are constructed: *GENERAL 0–1* takes on the value 1 if the firm uses none or one information source. The dummy variable *GENERAL 2–3* is coded one if it uses two or three sources and *GENERAL>3* is coded one if more than three information sources are used. The most densely populated category is that of 2–3 information sources (36 percent of the observations) which hence serves as the base category.

Indicators for R&D productivity

Following Levin and Reiss (1988), I assume that sectors closely related to science stay at the beginning of their development so that they find themselves in areas of R&D production with high marginal returns. Hence, sectors closely related to science are to be considered as sectors with high R&D productivity. In turn, sectors closely related to product markets are to be considered as sectors with low R&D productivity. I apply a canonical correlation analysis on the MIP–S questions on information sources to find common factors of the information sources already listed above. Associated firms and management consultancy firms are left out in the canonical analysis since it is not clear to what these sources are actually related. 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 assumption 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 to avoid potential multicollinearity problems with the proxy variables for the generality of the R&D approach. The R&D productivity terms 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. Changes in market demand is considered in the empirical model by firms' export shares, EXS, since an expansion 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 an 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

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

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 diversified a firm is with respect to its product range.

This variable is included in the innovation expenditure equation since firms which are more diversified 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.[19] is 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 the empirical model are presented in Appendix B.

[19] In earlier specifications, I also included the square of the logarithm of the number of employees. The squared term, however, did not turn out to be significantly different from zero in any of the specifications. Furthermore, both the square and the linear term carried the same sign.

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 the theoretical model as summarized in section 2.6.

How can the theoretical model be implemented empirically? The 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 a firm's research investment expenditures. 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 1 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.

Figure 1 shows that the category 'horizontal' cooperation is thinly populated, both in absolute terms and in relation to the other choices. I therefore combine the horizontal choice and the 'mixed' cooperation mode.[20]

It is important to note that the representation by a decision tree as in Figure 1 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

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

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.[21] It is thus desirable to have a flexible econometric technique at hand which nests these types of discrete choice models. Such an estimator has been proposed by van Ophem and Schram (1997), who show that the simultaneous and the sequential logit model can be combined without losing 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 is determined by the maximum utility to be obtained in the lower stage leading to the MNL as an 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.

Fig. 1. Population of the alternative cooperation modes in absolute (relative) terms.

The empirical model of cooperation choice includes the following variables: horizontal and vertical spillovers in natural logarithms, $ln(S^h)$ and $ln(S^v)$, the R&D generality–approach variables *GENERAL 0–1* and *GENERAL>3*, 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 $LSIZE$ as well as two sector affiliation dummy variables $TRANS$ and BRS (business–related services).[22]

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

[22]Earlier specifications also included the squared number of ln(employees). The coefficient of this term, however, carried to same sign as the linear term and was insignificantly different from zero in all specifications.

Estimation results of the cooperation choice are presented in Table 1. Besides the estimated coefficients and the related standard error, this table also contains the marginal effect of a one percent change of the related variable on the choice of the cooperation modes. Spillovers have an insignificant effect both on RJV formation and on the decision between vertical and mixed cooperation. Consistent with the theoretical model, proximity to scientific information — i.e., high research productivity — has a significantly positive effect on RJV formation. The estimation results also suggest that an increase in the generality of the research approach leads to an increased propensity of RJV formation. The more general a firm's research approach is, the more likely it is that this firm cooperates with a vertical cooperation partner. R&D productivity, firm size, sectoral affiliation and the generality of the research approach have a jointly significant impact on RJV formation.
With respect to the decision whether to conduct research in cooperation in a vertical or a mixed mode, weakly significant differences between East and West German firms are found. Firms from the business–related services sector tend to be more often involved in horizontal cooperations than firms from the trade sector. Lastly, firms following more general research approaches are more likely to conduct research in a mixed mode.
The goodness–of–fit of the specification displayed in Table 1 is modest. The McFadden (1974) Likelihood ratio index is 0.058, the McFadden Likelihood ratio index with the Aldrich and Nelson (1989) correction for the number of observations being applied is 0.053. 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 -2.8152 and hence is outside the (0,1) range. 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 of 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 estimated 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.[23] Further, normality of the simulated residuals could not be rejected at the usual significance levels.[24]
In the second stage, I run an OLS regression of the natural logarithm of innovation expenditures on the variables already included in the cooperation choice equation and the $SALES$–dummy variables. Since the spillover pool variables and firm size are also included as natural logarithms, the coefficients related to these terms represent elasticities. The coefficients corresponding to the other variables represent growth rates.
A first striking result 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 0.546) significant so that the variance–covariance matrix of the two–step procedure is consistently estimated.
The estimation results show that the effect of research cooperation on innovation intensity is positive and weakly significant. On the average of the involved firms, innovation intensity increases by 17.97 percent (median: 19.61 percent) if a firm is involved in an RJV. The associated standard error across firms is 11.35 percent (p–value 0.0566). With respect to the theoretical model, condition (14), which denotes the condition under which innovation effort under RJV is larger than under innovation competition, is met empirically.
The estimation results also indicate a significantly positive impact of horizontal spillovers on innovation intensity. The impact of vertical spillovers is insignificant and positive. Consistent with the theoretical model, innovation productivity as measured by the variable $SCIENCE$ is positive (but insignificant) while its counterpart proximity to market $PRIVATE$ is significantly negative. The productivity parameters are jointly significant at the one percent significance level indicating that innovation expenditures increase with increasing research productivity. 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 five percent significance level. The effect of the generality of the research approach is inversely U–shaped as indicated by the significant and negative dummy variables *GENERAL 0–1* and *GENERAL >3*.
The effects of the control variables for observable firm heterogeneity can be summarized as follows (only significant coefficients are considered): the innovation

[23] I also found that the correlations between the residuals and the explanatory variable (both linear and squared) are below 0.04 in absolute value.

[24] 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.

intensity of East German firms is significantly lower than that of West German firms. The elasticity of innovation expenditures with respect to firm size is 0.73 and is very accurately measured. The sector affiliation dummy variables turn out to be jointly significant. The coefficient related to the diversification index is positive and highly significant, indicating that more diversified firms invest more in innovation than less diversified firms. The dummy variables denoting past sales changes are jointly insignificant. Their signs indicate a nonlinear relationship between past sales changes and current innovation efforts.

In a last step of the analysis, I test if there are significant differences in the determinants of innovation expenditures between cooperating and non–cooperating firms. Therefore, I split up the sample into cooperating and non–cooperating firms and run the same regression for innovation intensity separately for cooperating and non–cooperating firms. By applying a Minimum Distance Estimation (MDE), I calculate a parameter vector which minimizes the weighted difference between the first–stage auxiliary parameter vectors and finally test whether there are significant differences in these auxiliary parameter vectors. 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 as well as the constants were left out in the MDE. The estimation results suggest that there are some large differences between the estimated parameter vectors related to cooperating and non–cooperating firms. In fact, equality of the parameter vectors cannot be accepted at the usual significance levels. This is, however, probably due to the imprecision with which the parameters for the cooperating firms are measured. And this is, in turn, due to the relatively low number of cooperating firms. Since there are, at least for the significant coefficients, 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.
The empirical findings can be summarized as follows:

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

(2) Spillovers appear to be as large enough to satisfy condition (14) from the theoretical model. The innovation intensity of cooperating firms weakly significantly larger for cooperating than for non–cooperating firms.

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

(4) The effect of the generality of the research approach is inversely U–shaped.

The theoretical model predicts a positive impact provided that the research approach is sufficiently general.

(5) In accordance with the theoretical model, market demand has a positive effect on research efforts.

(6) As predicted by the theoretical model, an increase in research productivity leads to an increase in the propensity to cooperatively conduct research.

(7) Research spillovers do not have a significant effect on RJV formation.

(8) The effect of research spillovers on innovation intensity is significantly positive.

(9) Market demand does not have a significant effect on RJV formation.

5 Conclusion

This paper presents a three–stage Cournot duopoly game for R&D cooperation, R&D expenditure and product market competition. In this model, the amount of knowledge of firm i freely available to firm j, e.g., the amount of spillovers, is made dependent on firm j's own innovation effort and on the generality of the research approach pursued.

Main results derived from the theoretical model are that if spillovers 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. Research productivity increases both the propensity to form an RJV and research expenditures.

In the empirical part of this paper, the implications of the theoretical model are tested using innovation survey data. While existing analyses are restricted to manufacturing industries, this study provides evidence for the service sector. A main finding of the empirical analysis is that innovation efforts under RJV are weakly significantly larger under RJV than under research competition. Consistent with the theoretical model, it is shown that an increase in market demand as well as in research productivity leads to an increase in innovation effort. In accordance with the theoretical model, cooperations are more often found between vertically rather than between horizontally related firms. The theoretical model predicts a positive impact of the generality of the research approach on research expenditures, provided that the research approach is sufficiently general. Instead, the data reveal that the effect is inversely U–shaped. An increase in research productivity leads to both an increase in research expenditures and to an increased likelihood of RJV formation. An increase in horizontal spillovers increases research expenditures as well. To summarize, the empirical findings are

broadly consistent with the theoretical model.
Further research will be devoted to shifting the theoretical model closer to reality. Therefore, my future innovation efforts will focus on extending the model to an oligopoly game and allowing the model to capture product innovation. Future research will also capture Bertrand instead of Cournot competition on the product market. 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) base: P(cooperation)			**P(mixed cooperating) base: P(vert. cooperating)**		
	Coeff.	Std. err.	mean marg. eff. (%)	Coeff.	Std. err.	mean marg. eff. (%)
$ln(S^h)$	-0.0527	0.1564	-2.322	-0.1106	0.1197	2.563
$ln(S^v)$	-1.1305	1.1031	-9.927	0.1594	2.2076	-3.697
$PRIVATE$	-0.4861	0.6381	-9.394	-0.2567	0.8799	5.951
$SCIENCE$	-1.3363***	0.4664	-17.301	-0.1647	0.7668	3.819
EXS	0.4370	0.7889	-4.183	-0.5705	0.9256	13.229
$EAST$	-0.4842	0.6636		0.5172*	0.3935	
$LSIZE$	-0.1953***	0.0666	-1.755	0.0250	0.1165	-0.580
$TRANS$	-1.4779**	0.7502		-0.4716	0.9294	
BRS	-0.2213	1.4066		-1.0797**	0.6781	
$GENERAL\ 0-1$	-0.0851	0.5033		0.3806	0.4825	
$GENERAL\ >\ 3$	-1.2022*	0.8470		0.6744**	0.3953	
$CONSTANT$	13.9673**	8.1473		0.4303	14.7518	
κ	-2.8162	2.4383				
F–Tests for joint significancy						
Spillover pools	1.128			0.990		
Productivity	8.241**			0.124		
Sector dummies	13.889***			3.756		
Generality	8.772***			2.912		
Pseudo R^2 and # of obs.						
pseudo R^2	0.058					
# of obs.	1,200					

***, **, * significant at the 1, 5 and 10 percent significance level, respectively.
Marginal effects are presented for the continuous variables only.

Table 2
Simultaneous model for cooperation and innovation intensity

	Coeff.	Std. err.
$ln(S^h)$	0.0800**	0.0420
$ln(S^v)$	0.3353	0.4694
$PRIVATE$	-0.6660***	0.2697
$SCIENCE$	0.3889	0.3534
EXS	0.3673**	0.2293
$EAST$	-0.2031**	0.0980
$TRANS$	0.4892	0.4138
BRS	-0.1715	0.3383
$LSIZE$	0.7281***	0.0440
$DIVERS$	0.3246***	0.1055
$GENERAL\ 0-1$	-0.2240**	0.1222
$GENERAL\ >\ 3$	-0.2223**	0.1068
$SALES--$	-0.2643*	0.1889
$SALES-$	0.0513	0.1297
$SALES+$	-0.0750	0.1088
$SALES++$	0.0428	0.1331
$CONSTANT$	-5.8514*	3.8906
D	0.4273	1.2828
$\rho\sigma_u\hat{\mu}D$	-0.0146	0.6459
$\rho\sigma_u\hat{\lambda}(D-1)$	-0.9077	1.2066
F–Tests for joint significancy		
$\rho\sigma_u\hat{\lambda}(D-1)$, $\rho\sigma_u\hat{\lambda}(D-1)$	0.5460	
Spillover–pools	1.8473	
Productivity	4.9989***	
Sector dummies	11.2852***	
Generality	3.6743**	
Sales dummies	0.9676	
Adj. R^2 and # of obs.		
adj. R^2	0.4555	
# of obs.	1,200	

***, **, * significant at the 1, 5 and 10 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.
$ln(S^h)$	0.5294	0.9734	0.0799**	0.0459	0.0783**	0.0463
$ln(S^v)$	-0.1824	4.2865	0.3514	0.5106	0.6795*	0.54
$PRIVATE$	0.8035	4.1831	-0.6604***	0.2759	-0.531**	0.2928
$SCIENCE$	3.0522	7.1884	0.3906	0.3746	0.4127	0.3852
EXS	1.1391	1.3607	0.3649**	0.2261	0.3147*	0.2408
$EAST$	-0.7592	1.2963	-0.2029**	0.1005	-0.1995**	0.1049
$TRANS$	4.5170	9.7835	0.4916	0.4444	0.5386	0.4464
BRS	2.9392	7.9868	-0.1681	0.365	-0.0964	0.3671
$LSIZE$	0.8359	0.7477	0.7295***	0.0445	0.7587***	0.0459
$DIVERS$	0.7287	1.3275	0.3251***	0.1057	0.3318***	0.1116
$GENERAL\ 0-1$	-1.3557	1.8440	-0.2226**	0.1273	-0.1962*	0.1318
$GENERAL\ >\ 3$	0.0137	1.0309	-0.2214**	0.1096	-0.2048**	0.1171
$SALES--$	-0.8120*	0.5595	-0.2634*	0.179	-0.2525*	0.1902
$SALES-$	-0.4901*	0.3793	0.0538	0.1343	0.1005	0.1448
$SALES+$	-0.1180	0.3281	-0.076	0.1083	-0.1	0.1159
$SALES++$	-0.0622	0.3988	0.0417	0.1357	0.0125	0.1457
$CONSTANT$	-22.8406	87.3323			-8.6850**	4.3987
$HECKCORR$	3.6061	10.6190			0.6501	1.2720
R^2 and # of obs.						
pseudo R^2	0.379				0.4615	
# of obs.	162		1,200		1,038	

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

Appendix A: Linear combinations for canonical correlation

	Coeff.	Std. err.
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
fairs, 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.
$ln(innovation\ exenditures)$	-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	
$TRANS$	0.2970	
BRS	0.5231	
$LSIZE$	4.1900	1.7070
$GENERAL0--1$	0.3094	
$GENERAL > 3$	0.3349	
$DIVERS$	1.5486	0.5292
$SALES--$	0.0668	
$SALES-$	0.1601	
$SALES+$	0.4101	
$SALES++$	0.1526	

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 linearly dependent on a set of explanatory variables summarized in row vector $\boldsymbol{x_t}$:

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

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, $\omega_{no\ coop,i}$, $\omega_{vert(coop),i}$ and $\omega_{mix(coop),i}$ are independent. Unless $\kappa = 0$, $\omega_{coop,i}$ is correlated with $\omega_{vert(coop),i}$ 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 and 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.[25]

[25] The estimation of the van Ophem and Schram (1997) procedure and the simultaneous equation model as well as the Minimum Distance Estimation were performed using my own GAUSS program. A copy of the programs can be obtained from the author upon request.

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:

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

Appendix D: The simultaneous equations model

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

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

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

where $\boldsymbol{d}$ is a vector of parameters (relating the vector of explanatory variables $\boldsymbol{Z_i}$ to D_i^*).

The natural logarithm of innovation expenditures, henceforth denoted by $ln(INNOINT)$, 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:

$$ln(INNOINT_i) \;=\; \boldsymbol{X_i b} \;+\; cD_i \;+\; u_i, \tag{25}$$

where $\boldsymbol{d}$ and c relate $\boldsymbol{X_i}$ and D_i to $ln(INNOINT_i)$, 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

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

where σ_u and σ_v are the standard errors of the disturbance terms u_i and v_i, respectively, and that

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

The innovation intensity equation accounting for endogeneity of the cooperation decision is

$$\ln(\text{INNOINT})_i \;=\; \boldsymbol{X_i b} \;+\; cD_i \;+\; \rho\sigma_u\mu_i D_i \;-\; \rho\sigma_u\lambda_i(1-D_i) \;+\; v_i. \tag{28}$$

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 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 $ln(INNOINT_i)$, conditional on cooperation ($D_i = 1$), 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_i 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

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

and that

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

The likelihood function l is then given by

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

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 and applications are presented in Kodde et al. (1990). Minimum Distance Estimation involves the estimation of the R reduced form parameter vectors in a first stage. In the present case, these reduced form parameters are the parameter estimates obtained from running two separate OLS regressions for the innovation intensity of cooperating and non–cooperating firms. 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 $R \cdot K \;\times\; K$ matrix $\boldsymbol{H}$ imposes $(R-1) \cdot K$ restrictions on $\boldsymbol{\theta}$. The $R \cdot K \times 1$ vector $\hat{\boldsymbol{\theta}}$ contains the R stacked auxiliary parameter vectors. In the present case, $\boldsymbol{H}$ is defined by a $R \cdot K \times K$–dimensional stacked identity matrix. 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

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

with variance–covariance matrix

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

In the present case, where the two 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 consist of zero–matrices.
To test the null hypothesis that the R auxiliary parameter vectors coincide with one another, the following Wald–type test statistic can be applied:

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

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