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Collusion through Joint R&D: An Empirical Assessment

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Abstract: This paper tests whether upstream R&D cooperation leads to downstream collusion. We consider an oligopolistic setting where firms enter in research joint ventures (RJVs) to lower production costs or coordinate on collusion in the product market. We show that a sufficient condition for identifying collusive behavior is a decline in the market share of RJV-participating firms, which is also necessary and sufficient for a decrease in consumer welfare. Using information from the US National Cooperation Research Act, we estimate a market share equation correcting for the endogeneity of RJV participation and R&D expenditures. We find robust evidence that large networks between direct competitors – created through firms being members in several RJVs at the same time – are conducive to collusive outcomes in the product market which reduce consumer welfare. By contrast, RJVs among non-competitors are efficiency enhancing.

Keywords: Research Joint Ventures, Innovation, Collusion, NCRA

JEL Classification: K21, L24, L44, D22, O32

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1. Introduction

Joint R&D activities – such as research joint ventures (RJVs) – are a prominent phenomenon especially in many high-tech sectors of the economy, as they hold the potential to increase efficiency and promote innovation, which raises welfare and benefits consumers.[1] As a result, RJVs are frequently stimulated by governments around the world. At the same time, it is well-known that the benefits of R&D collaborations need to be re-assessed if such activities are used to achieve product market collusion. In other words, there exists a trade-off between upstream R&D cooperation and downstream competition if they are causally linked.

This paper tests whether research cooperation leads firms to coordinate in product markets using data available through the US National Cooperation Research Act (NCRA). The NCRA was introduced in 1984 to raise US competitiveness, in particular vis-à-vis Japanese firms. US firms were encouraged to establish research links, even if they were competitors in downstream product markets (Link, 1996; Jorde and Teece, 1990). Specifically, firms in NCRA-RJVs were granted milder antitrust scrutiny.[2] As a consequence, a substantial number of large-scale R&D groups have emerged.[3] Moreover, firms often participate in several of the NCRA-RJVs at the same time (Vonortas, 2000). Therefore, by making connections across RJVs, firms effectively create sizable networks. While possibly generating significant efficiencies, one may also wonder whether these extensive networks among competitors facilitate collusion in the product market (Brodley, 1990; Shapiro and Willig, 1990).[4]

While the early and much cited theoretical literature on RJVs gives support to an industrial policy approach by showing that joint R&D often leads to welfare improvements, an important aspect of these studies is the assumption that cooperation at the R&D stage does not lead to coordination in the product market (Brander and

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[1] See Cassiman and Veugelers (2002), Hernan, Marin and Siotis (2003), and Röller, Siebert and Tombak (2007) for empirical evidence.

[2] Among other advantages, authorities would apply the rule of reason instead of a per se illegality presumption to firms in an RJV filed under the NCRA.

[3] Jorde and Teece (1999, p82) argue: "A research joint venture may not do enough to overcome appropriability problems, unless many potential competitors are in the joint venture." This statement coincides with the intended purpose of US policy makers to include as many competitors as possible in the NCRA collaborations.

[4] For instance, in 1990 US antitrust authorities found six important oil companies that were also participating in the NCRA program guilty of sharing price information. See Coordinated Proceedings in Petroleum Products Antitrust Litigation, 906 F2d 432 (9th Cir. 1990) and Petroleum Products Antitrust Litigation, 906 F.2d 432 (9th Cir. 1990), and Helland and Goeree (2010) for a discussion of this case.

Spencer 1983; Spence 1984; Katz, 1986; Kamien, Muller and Zang, 1992).[5] More recent contributions, however, show that when firms are allowed to cooperate in the product market, RJV-participation helps in sustaining collusion therein. This can occur through several mechanisms. First, RJVs can be facilitating vehicles which create common assets – and therefore common interests – among participating firms and therefore provide a new credible punishment device (Cabral, 2000; Martin, 1995).[6] Second, through the sharing of research findings, RJVs may reduce cost asymmetries among firms and hence make product market agreements more stable (Miyagiwa, 2009). And third, RJVs can be used for the transmission of information to signal cooperative behavior (Cooper and Ross, 2009). These theoretical arguments thus show that there are various channels through which R&D collaboration may facilitate product market coordination.

This paper proposes an empirical test of whether RJVs have led to collusion, explicitly taking into account that firms may have different reasons for joining. In particular, we allow for an oligopolistic market, where firms participate in RJVs for either efficiency or collusive reasons. In this context, one can show that an empirically tractable condition exists that identifies the welfare implications of joint R&D activities, namely whether the market share of the participating firms (insiders) changes with being a member in an RJV. Specifically, it is argued that a sufficient condition for identifying collusive behavior is an insiders' declining market share with respect to non-participating rivals. A lower insider market share is also necessary and sufficient for a decrease in consumer welfare.

This test is then applied to the NCRA data by estimating an autoregressive market share equation with dynamic panel data techniques. We control for the endogeneity of research collaboration through predetermined drivers of RJV-participation. The advantage of our approach of testing the competitive impact of RJVs via market shares is that one does not need data on prices, costs, and elasticities, which are frequently not available, not reliable, or difficult to measure.

[5] An early exception is d'Aspremont and Jacquemin (1988) who consider a duopoly model of R&D coordination and find that welfare is often reduced if firms also collude in the product market.

[6] This idea is reminiscent of Bernheim and Whinston's (1990) theory of multi-market contact: firms that interact in more than one market may be able to sustain collusion more easily by reducing overall asymmetries. Spagnolo (1999) further shows that multi-market contact can facilitate coordination because when firms are present in more markets then the lost profits from deviation increase faster than the gains from deviation.

There are few empirical studies on the relationship between R&D cooperation and collusion. Our empirical methodology is closest to Gugler and Siebert's (2007) study, which compares mergers to RJVs. These authors estimate an endogenous switching regression model and find no differences between the two modes of cooperation in their effect on market shares. However, they do not allow for the heterogeneous effects of RJV-participation while it is unlikely that all types of R&D collaborations are used for product market coordination.

Helland and Goeree (2010) investigate whether a toughening of the US leniency program in 1993 motivated a decline in RJV-participation under the NCRA program. The underlying idea is that if firms use the NCRA-RJVs as a collusive tool, then tougher antitrust sanctions should make firms more cautious. By finding that fewer firms enter, they conclude that the NCRA-program has led to collusion.[7]

By contrast, our approach differs from the above work by relying on market shares, which in turn makes it possible to distinguish between collusion and efficiency, as well as to make a welfare assessment. The heterogeneous effects of RJV-participation are also explicitly considered. Specifically, we distinguish between RJVs amongst firms that are not competing in the same product market ("vertical RJVs"), which are more likely to be only efficiency enhancing, and RJVs that include direct competitors ("horizontal RJVs"), which are potential vehicles for collusion.[8] As an aside, note that the term "vertical RJV" is used as a contrast to the horizontal RJVs. It is, however, not necessarily the case that these RJVs consist of firms that are vertically linked in product markets; there may be no relation at all.

Furthermore, we take into account that firms frequently participate in several horizontal RJVs, thereby creating networks amongst direct competitors that in some instances include a substantial part of the industry.[9] In sum, our approach incorporates aspects of both the size and scope of research collaborations.

Our empirical results can be summarized as follows. On average, RJV-participation does not lead to a significant change in market shares, which suggests

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[7] Note further that in an experimental setting Suetens (2008) finds that R&D cooperation indeed facilitates price collusion.

[8] Examples of competitors involved in the same NCRA-RJVs include Texaco and Chevron in the petroleum industry, Apple and Dell in the computer industry, Texas Instruments and AMD in the semiconductor industry, and Burlington Northern Santa Fe and Union Pacific in the railroad industry.

[9] In the petroleum industry, for instance, six direct competitors are connected through their participation in several NCRA-RJVs. The formed networks are even larger in other industries; sixteen competitors are connected in the computer industry and twenty one in the special-industry-machinery sector.

that some RJVs are used for innovation and others mainly for collusive purposes. By contrast, vertical RJVs lead to a significant increase in market shares, which corresponds to the view that non-competing firms enter RJVs to realize efficiency gains. RJVs amongst competitors display a decline in market share, indicating collusion and lower consumer surplus. This result on horizontal RJVs becomes statistically stronger when the network structure is also taken into account: sufficiently large horizontal networks lead to a significant drop in market share. These findings suggest that it is the nature and size of the formed network that drives the welfare aspects of RJV cooperation. Empirically, we estimate the horizontal network size above which it becomes problematic in terms of collusion when it includes 18% or more of its direct competitors. Overall, our results are in line with the conjecture that joint R&D activities can lead to collusion in the product market, in particular when a large number of direct competitors are involved.

The setup of the paper is as follows. The next section introduces the formal framework, where our theoretical identification strategy is presented. Section 3 describes the data and characterizes the network formation through RJV participation. Section 4 develops the empirical estimation strategy, and Section 5 explains the results. Finally, Section 6 concludes.

2. Formal framework

We give a formal reasoning of how collusion through R&D collaboration impacts a participating firm's (net) market share and consumer welfare, taking into account that these cooperations may be used for innovative purposes, for collusion, or for both. Our setting allows for firms competing in quantities, but we later argue that the same identification strategy also works when firms compete in prices. For quantity competition, the setup of Farrell and Shapiro (1990) is closely followed, as this is one of the most general inter-firm collaboration models in terms of demand and supply specification.[10] We further discuss some of the more restrictive assumptions of this model and argue that the results would stay qualitatively the same by relaxing these conditions.

[10] Although theirs is a merger model, the same argumentation can be used for firms colluding through RJVs, not taking into account *how* exactly firms use RJVs as a collusive device, which is outside the scope of this paper. In other words, we abstract from all internal stability issues of collusion; see e.g. Cabral (2000) and Cooper and Ross (2009) for self-enforcing agreements through RJV membership.

A basic framework: quantity competition

We begin with an explanation of the general mechanism. Consider a market with N firms competing à la Cournot in homogenous goods. Demand is given by $p(X)$, where p is price, X is industry output, and $p'(X) < 0$. We denote a firm i's cost function by $c(x_i)$, where x_i is firm i's output, and $c_x(x_i)$ its marginal cost. The first-order condition is then $p(X) + x_i p'(X) - c_x(x_i) = 0$ and the Cournot equilibrium is a vector $(x_1,...,x_N)$ such that the first-order condition holds for all N firms. When imposing two standard conditions on the Cournot equilibrium to ensure uniqueness, one can show that:[11]

<u>Lemma 1</u>: W*hen firms compete à la Cournot, then an exogenous output change by a group of K<N firms moves aggregate output in the same direction, but by less.*

This Lemma is the "workhorse" for further analysis. We now focus on RJVs and start with the case where firms enter an RJV only for innovation purposes. Participation then leads to a lower marginal cost function $c_{RJV}(x_i) \le c_x(x_i)$ for each of the K participating firms (insiders).[12] As a consequence, each of the K insiders increases output, which naturally follows from the first-order condition.[13] In response, the remaining N-K rivals (outsiders) lower their production accordingly to re-establish the Cournot equilibrium. Therefore, insiders' market share rises with respect to the outsiders. Of course, by Lemma 1, total production X increases as well. Therefore, given that $p'(X) < 0$, consumer welfare rises when firms participate in RJVs solely for innovation reasons.

On the other hand, when firms use RJVs only for collusion, the K insiders, by jointly deciding upon production levels in the product market, use their enhanced

[11] Given that this and further proofs are straightforward extensions of Farrell and Shapiro (1990), they are left out for reasons of space. The first condition imposes downward sloping reaction curves, $p'(X) + x_i p''(X) < 0.$ The second condition states that each firm's residual demand curve intersects its marginal cost curve from above, $c_{xx}(x_i) > p'(X).$

[12] The assumption that NCRA-RJVs mainly lead to cost reductions rather than to the introduction of new products is in accordance with their intended purposes (Link, 1996). As is also argued in Gugler and Siebert (2007), many articles and case studies of RJVs confirm that the vast majority of RJVs focus (exclusively) on the development of new technologies resulting in cost reductions. Examples for the NCRA-RJVS include Link (1996) and Röller et al. (2007). Moreover, case studies by Chang and Podolny (2002), Silverman (2002) and Yoffie (2005) describe how RJVs focus on process innovation.

[13] It is assumed for now that firms have ex-ante identical cost functions; the K participants therefore expand their production in the same way.

market power to lower output. The *N-K* outsiders respond by increasing theirs. Insiders' market share thus goes down with respect to the outsiders. Further, given that the total production decreases (Lemma 1), prices increase and consumer welfare, hence, is lower.

Since firms potentially enter RJVs *both* for collusive and innovation purposes, the effects on insiders' market shares, equilibrium production and equilibrium prices is a priori ambivalent. Nevertheless, it is possible to identify a net effect. A group of *K* colluding insiders decrease their production if the following holds: the total mark-up of the *K* firms should be less than the sum of their pre-RJV mark-ups, keeping their production constant at the pre-RJV level.[14] In other words, insiders decrease production if and only if $p - c_{RJV}(\sum^{K} \bar{x}_i) \leq \sum^{K} \left[p - c_x(\bar{x}_i) \right]$, where p is the pre-RJV price, the cost functions c_x are measured at pre-RJV output levels $\bar{x}_i$, and c_{RJV} is measured at total pre-RJV output $\sum^{K} \bar{x}_i$. As a consequence, *K* colluding RJV members lead, relative to the pre-RJV situation, to a decrease in output when

$$(1) \qquad \frac{\sum^{K} c_x(\bar{x}_i) - c_{RJV}(\sum^{K} \bar{x}_i)}{K-1} \leq p .$$

As a consequence of firms' first-order condition, the market shares of the *K* insiders then decline with respect to the *N-K* outsiders and, by Lemma 1, total output decreases. Therefore, when inequality (1) is satisfied, *K* firms participate in RJVs and collusive effects dominate innovation, resulting in declining market shares.

Thus, we can state the theoretical identification condition for collusion.

<u>*Identification*</u>*: A necessary condition for firms to collude through RJV participation is a decrease in market share with respect to their non-participating rivals. When this occurs, the product market price rises, leading to a decrease in consumer welfare.*

[14] This is a reinterpretation of Proposition 1 of Farrell and Shapiro (1990, p. 112) for RJVs, extending their reasoning from 2 to *K* firms.

Extensions of the basic framework

The qualitative implications of our framework remain the same when relaxing its assumptions. First, the model assumes homogenous goods. As products become more differentiated, firms impose fewer negative externalities on each other and consequently reduce their output by less when colluding through RJV-participation. Insiders then gain less by colluding and as a consequence seek a lower increase in price. Therefore, a lower degree of innovation is needed to offset collusive effects, as Gugler and Siebert (2007) also show in a merger model with linear demand. Thus, while having an influence on exactly how much innovation neutralizes collusion, the predictions on market shares are robust to any degree of product differentiation.

Second, although our setup assumes for simplicity that firms exhibit ex-ante symmetric cost-functions, the above condition –while potentially not holding for *each* of the RJV-participating firms– still holds *on average* for the K insiders when these firms have ex-ante asymmetric cost functions, as long as this distribution of cost functions is not too dispersed. It is this average effect that is needed for our empirical application.

Further, we do not model firms' choice of R&D-levels when entering an RJV for innovation. That is, it is assumed that it is always profitable for firms in "only-innovation-RJVs" to invest in a lower marginal cost. If firms are profit-maximizers, this assumption is logically satisfied. Indeed, then firms only enter an innovation-RJV when this is profitable and, absent collusive effects, these RJVs should thus lead to a lower marginal cost. In any case, this assumption will be empirically confirmed: firms that enter in vertical RJVs – i.e. RJVs that are set up amongst non-competitors and are thus hardly intended for collusive purposes – exhibit (i) an increase in R&D spending and (ii) a higher resulting market share, which is consistent with these firms having invested in R&D to reach a lower marginal cost of production.[15]

[15] Note that these empirical observations are also consistent with a more complex model where both RJV insiders and outsiders have the possibility to invest in R&D. When R&D is characterized by strategic complementarities, then the average R&D spending for insiders should be higher than for outsiders, leading to a relatively lower marginal cost for participants, as Banal-Estañol, Macho-Stadler and Seldeslachts (2008) show in a merger context. The same work also considers an endogenous merger-model where R&D-spending is a strategic variable, which is equivalent to firms entering in RJVs for collusive purposes and deciding whether to innovate as well. When R&D is hard to organize among participating firms or too costly relative to its benefits, then firms cooperate in the product market but won't innovate, which leads to a loss in market share. If, on the other hand, participating firms both cooperate in the product market and innovate, then their market shares increase vis-à-vis outsiders. These results, therefore, indicate that a more elaborated RJV setup than ours would yield the same empirical identification.

We briefly explain the reasoning when firms compete in prices and products are differentiated.[16] Assume again that the strategic variable –price in this setting– moves more by the initial decision of a group of K firms than by the reaction of their N-K rivals, which is again a necessary condition to reach a unique equilibrium (see for example Vives, 1985, for an extensive discussion). When firms enter an RJV purely for innovation reasons, marginal costs decrease. As a result, the insiders set lower prices. Rivals react by setting lower prices as well, given that price-setting exhibits strategic complementarities (Fudenberg and Tirole, 1984). However, given that the reaction by outsiders is not as strong as the initial price decrease, insiders capture a larger part of the market. Therefore, they gain market share and consumer welfare increases. If, on the other hand, firms participate purely for collusive reasons, insiders raise prices (or, equivalently, contract output). Rivals react by increasing prices as well, but by less; thus contracting output by less. Therefore, insiders lose market share with respect to their rivals and, at the same time, consumer welfare decreases due to higher product market prices. If, finally, RJV-participation induces firms to both reduce costs and to collude, when collusion dominates cost reduction it must logically be that (i) insiders lose market share and (ii) consumer welfare decreases. Our identification, therefore, is the same as when firms compete in quantities.

Note that the above analysis on market shares of insiders vis-à-vis their non-participating rivals assumes partial collusion, i.e. restrictive agreements are formed among competitors that involve a subset of the industry. Although most theoretical works on cartels assume the monopolization of the industry, partial cartels have often occurred in reality. For example, three North-American and five European firms in the citric acid industry were fined for fixing prices and allocating sales in the worldwide market. Their joint market share was around 60 percent (Levenstein and Suslow, 2006). Also, a cartel among shipping firms in the North Atlantic constituted 75% of the market (Escrihuela-Villar, 2003). Recently, a small but growing theoretical literature has also started to examine partial cartels. Bos and Harrington (2010), for example, consider the endogenous formation of cartels and find that the optimal cartel size in an industry is less than all-inclusive when colluding is costly or firms are sufficiently patient, and colluding firms are relatively large with respect to their non-colluding rivals. Escrihuela-Villar (2008) determines that a partial cartel is

[16] Price competition in homogenous goods yields non-continuities and it is often hard to interpret results; see Vives (1999) for a discussion.

internally and externally stable because allowing more members would increase the incentives for each to deviate and undercut the collusive price. In sum, both empirical evidence and theory confirm that partial collusion is profitable.

3. Data

Our data is based on three sources: the NCRA-RJV database, which holds information on RJVs and its participants under the National Cooperative Research Act (1985-1999), the Compustat North America database containing firm-specific information on about 22,000 publicly traded US firms (1986-1999), and the NBER US Patent Citations Data File. The starting point is all 785 NCRA-RJVs registered in the period 1985-1999 involving 5,755 for-profit entities. There are also non-profit entities in some NCRA-RJVS, but since these are not relevant for the purpose of this paper, they will not be considered.

We provide a short overview of the NCRA-RJV data – for a detailed explanation see Link (1996) and Vonortas (1997).[17] The enactment of the NCRA in 1984 and its amended version, the National Cooperative Research and Production Act (NCRPA), have been created to stimulate R&D in the US. In particular, the act allows American firms to establish large RJVs that conduct pre-competitive R&D and has been implemented by the US Congress as part of an industrial policy to improve international competitiveness of American companies and industries.[18] Under the terms of the NCRA, a notice must be filed with both the US Department of Justice and the Federal Trade Commission disclosing the RJV's principal research content and its initial members; subsequent notifications of changes in membership or research intent are also required. In return, certain antitrust exemptions are granted to the NCRA-RJVs, such as, for example, the application of the rule of reason instead of the per se rule and the exemption from treble damages when illegal behavior is found.

In order to obtain firm- and industry-level measures, we match 1,013 out of the original 5,755 NCRA for-profit entities to firms in the COMPUSTAT North America database. The dropped firms are mostly small and, in a few cases, non-US

[17] We thank Nicolas Vonortas from George Washington University for making this data available to us.

[18] Accordingly, an RJV may be filed under the NCRA when its purposes are "(a) theoretical analysis, experimentation, or systematic study of phenomena or observable facts, (b) the development or testing of basic engineering techniques, (c) the extension of investigative finding or theory of a scientific or technical nature into practical application for experimental and demonstration purposes..., (d) the collection, exchange, and analysis of research information, or (e) any combination of the [above]." (Link, 1996)

firms. The remaining companies constitute our sample of RJV participants. We then tie 630 out of the 1,013 entities to the NBER US Patent Citations Data File, containing all filed US patents since 1963. This means that the other 383 RJV insiders do not hold any patent. As explained in the next section in more detail, the reason for matching RJV insiders with the patent database is because patents are an important tool in our strategy to instrument for research collaboration.

The sample of outsiders in an industry in a given year is generated by taking all those firms which did not participate in any RJV in that industry and the given year, where an "industry" is defined according to firms' primary SIC4 codes. We exclude the firms that compete in industries with no RJV from our sample of outsiders, since these firms do not face any insiders.[19] Out of these 9,597 unique outsiders, we match 1,355 to patent data. The other outsiders are assigned zero patents.

In sum, we generate a sufficiently large sample of both NCRA-COMPUSTAT insiders and non-NCRA COMPUSTAT outsiders with information about their patent activities. Unfortunately, COMPUSTAT does not provide complete series on the included variables; we therefore drop all those firms-observations for which we have missing values on sales, as this variable is needed to define a firm's market share. Finally, those industries where the number of firms is lower than 3 are dropped as these are considered to be outliers. The final sample, i.e. the included firms over the period 1986-1999, is an unbalanced panel with on average 430 insider-year observations (ranging from 130 in 1986 to 732 in 1999) and 5,435 outsider-year observations (ranging from 4,102 in 1986 to 6,765 in 1999).

The variables "market share" and "research collaboration" are two important variables in our analysis below, and are thus first discussed. Market shares are constructed by using firms' sales as reported in their primary 4-digit standard industry classification (SIC4), which is equivalent to the currently used 6-digit NAICS level.[20] This aggregation level represents the most detailed industry classification possible on the basis of SIC codes. The definition of the relevant product market is always an issue in antitrust. Although we use 4-digit SIC classifications, it is possible that the

[19] To be precise, the firms in these industries are not included in the main analysis, but are used in a test of the exclusion restrictions for our instruments.
[20] The market share of a firm is defined as the firm's yearly sales divided by the sum of yearly sales in its primary SIC4 industry (see Table 1 for the precise definition).

relevant antitrust market is smaller.[21] If so, effects would be underestimated, as they are likely to be larger in smaller markets. In this case our estimates are a lower bound.

Our first measure of RJV participation is based purely on whether a firm is participating in at least one RJV ("RJV any"). Since it is more likely that collusive effects are present when firms are competitors, we then define a variable "RJV horizontal", which is relevant when a firm meets at least one competitor in this RJV, where competitors are defined as firms competing in the same SIC4 industry. We also define a variable "RJV vertical" when *no* members in the RJV are competitors.

Table 2a provides summary statistics in which some first patterns can be observed. Firms that do not enter RJVs are smaller in terms of market shares, total assets, R&D expenditures and patent stock. [22] In particular, the difference between insiders and outsiders for the latter two innovation-variables is substantial, suggesting that these might be factors related to participation decisions. If we partition the RJV insiders in those that participate in either vertical or horizontal RJVs, we observe that the members in horizontal RJVs are larger in terms of total assets, R&D expenditures and patent stock, yet they are smaller in terms of market shares.

[Insert Table 2a about here]

To further identify the collusive nature of RJV cooperations, more precise measures for horizontal RJVs are then defined. One possibility would be to look at the number of direct competitors in an RJV (see Helland and Goeree, 2010). Yet, about one-third of all insiders collaborate in several NCRA-RJVs – the mean being 4.02 RJVs per participating firm – thereby effectively creating networks. For example, in the petroleum industry Chevron, Amoco, Exxon and Texaco all participate in more than 70 NCRA-RJVs; in the semiconductor industry Intel and Texas Instruments are members in 20 and 18 RJVs, respectively; and in the computer industry IBM, Hewlett Packard and Apple have joined more than 20 research collaborations.

This network dimension might be especially relevant when investigating collusive effects, as product market coordination often works through competitors

[21] The median number of firms in a given SIC4 industry is 34. It is difficult to say in general how many firms operate in an antitrust market. As an example, in a study containing 150 European horizontal merger cases, Duso et al. (2007) find that the European Commission identified about 8 rivals to the 2 merging firms, which thus indicates that on average an antitrust market consists of 10 firms in Europe.

[22] To build the patent stock of firm i at time t we use a constant knowledge depreciation rate of 0.15 (see e.g. Hall, 1990, and Griliches and Mairesse, 1984).

creating several formal meeting points. A sufficiently large horizontal network may then give insiders the critical mass to make collusion sustainable. Indeed, as Bos and Harrington (2010) and Escrihuela-Villar (2008) indicate, although partial collusive networks are stable, they need to be large enough to be profitable.[23] Further, the punishment potential may be higher when forming a network through participation in several RJVs, as the multi-project argument of Vonortas (2000) indicates, and collusion may thus be easier to sustain.

The size of the network may also matter for innovation. If firms participate in RJVs to increase their efficiency then a bigger research network might lead to a higher cost-reduction, for example, through a larger pool of knowledge (Veugelers, 1998) or by benefiting more from learning effects (Hoang and Rothaermel, 2005). On the other hand, a larger network may lead to higher agency costs and more severe free-riding (Duso, Pennings and Seldeslachts, 2010). If this is the case, then one could erroneously link a loss in market share to collusion. In order to exclude this possibility, we will test whether firms in larger vertical networks – i.e. research networks among non-competitors – enjoy a larger market share gain. This will turn out to be the case, which means that firms in larger innovation networks enjoy higher efficiency gains.

In sum, the above discussion suggests that by taking the size of the horizontal network into account a more precise identification of our question whether firms use RJVs for collusive or for innovation purposes is obtained.

We construct a horizontal network measure as the number of unique competitors a firm meets in all the RJVs in which it is a member, and divide this figure by the total number of competitors in the industry, which gives us a measure of the "market coverage" of a firm through its RJV-participation. Therefore, the relative size of firm *i*'s horizontal network in an industry *m* in year *t* is defined as

$$(2) \qquad Horizontal\ Net_{imt} = \frac{1}{N_{mt} - 1} \sum_{j \neq i} contact_{ijt} ,$$

where N_{mt} is the number of firms present in year *t* in market *m* and

$$contact_{ijt} = \begin{cases} 1 & \text{if in year } t \text{ firm } i \text{ meets competitor } j \text{ in at least one RJV} \\ 0 & \text{otherwise} \end{cases} .$$

[23] Equivalently, Salant, Switzer and Reynolds (1983) show in a merger-context that a merger without efficiency gains, which is equivalent to our setup where firms collude and do not innovate, are only profitable when the merger consists of a sufficiently large number of firms present in the industry.

Since the maximum number of contacts a firm *i* can have with its competitors *j* in the market is the total number of firms in the industry minus one, i.e. $N_{mt}-1$, we must necessarily have that $Horizontal\ \ Net_{imt} \in [0,1]$.[24]

As discussed above, the links with competitors through membership in a single RJV are likely to be less numerous than when taking into account a firm's participation in several RJVs. To illustrate this point, we compare our network measure, as specified in equation (2), with two RJV-specific measures of a firm's connectivity. First, the average number of competitors a firm meets in horizontal RJVs is calculated relative to the total number of competitors in the industry ("average horizontal RJV"). Second, the maximum of a firm's links of all horizontal RJVs in which it is an insider is obtained, again relative to the number of firms in its sector ("largest horizontal RJV").

On average, our horizontal network variable equals 0.148, which implies that the average firm that participates in horizontal RJVs creates a network with its competitors that covers 14.8% of the industry. On the other hand, the average coverage per horizontal RJV is 0.082, while the relative number of links in a firm's largest horizontal RJV has as mean 0.098. When testing the difference between the means of the two RJV-related measures and of our horizontal network variable, the latter is found to be significantly larger at the 1% significance level.

To further demonstrate this issue, we look at the petroleum industry (SIC4=2911), where firms were effectively convicted for collusion. In 1999, for example, Chevron meets 9 of its 31 competitors through participation in several RJVs (the horizontal network size is therefore 0.29), while it links only with a maximum of 5 in a single RJV, which implies an industry coverage of just 0.166. Exactly the same pattern can be observed for Texaco and Exxon. Another example is the semiconductor industry (SIC4=3674) in 1997, where Texas instruments meets 22 out of 127 firms in several horizontal RJVs, thereby creating a horizontal network of 0.173, whereas it only meets 11 of these competitors in one RJV, implying a coverage of 0.086. Virtually the same differences can be noted for other important firms in the semiconductor industry, as for instance Intel and AMD. These findings emphasize

[24] The reason we construct this variable as a relative measure, apart from the obvious scaling issues, is that our identification is a function of the size of the network relative to the industry (see equation 1, where p and $\overline{x}_i$ both depend on N).

that it is potentially important to account for the fact that a firm participates in several RJVs. By defining a horizontal network measure, one obtains an unbiased measure of a firm's effective connectivity with competitors, which we see as one of the main contributions of our approach.

Figure 1 shows that the distribution of horizontal networks is considerably skewed to the left, i.e. most networks are relatively small and cover, on average, 14.8% of the industry (see also the horizontal network variable in Table 2a). Based on this empirical distribution, we divide the networks into three size categories and define small networks as those that are in the lowest 25% percentile, medium-size are those that are in the 25%-75% range, while large networks are situated in the top 75%.[25]

[Insert Figure 1 about here]

Taking a first look at these data, some regularities emerge. Firms participating in small horizontal networks are smaller and less innovative –in terms of R&D expenditures and patent stock– than firms participating in medium-size networks, which in turn are smaller and less innovative than companies in large networks. This suggests a positive correlation between innovation variables, market shares, and size of the created horizontal network. However, in order to identify a true causal relationship, we revert to our econometric framework.

[Insert Table 2b about here]

4. Empirical implementation

The empirical challenge is to identify consumer welfare-enhancing participation for innovation reasons (which leads to output expansion vis-à-vis the rivals) and consumer welfare-decreasing participation for collusive reasons (which leads to output contraction with respect to the rivals).

Our test is implemented by estimating an autoregressive market share equation as a function of RJV participation, controlling for other factors that may potentially influence a firm's market share. Specifically, the following equation is estimated:

[25] These categories are arguably arbitrary. However, different size categories (as for instance based on the 33rd and 67th percentiles) do not qualitatively change our results.

$$(3) \quad MS_{imt} = \alpha_0 + \alpha_1 MS_{imt-1} + \sum_{\tau=0}^{2} \beta_\tau RJV_{imt-\tau} + \sum_{\tau=0}^{2} \gamma_\tau Log(R\,\&\,D)_{imt-\tau} + \lambda X_{mt-1} + \eta_{im} + \eta_t + \varepsilon_{ijt},$$

where MS_{imt}, our dependent variable, is the market share of firm *i* operating in industry *m* in year *t*. As independent variables, we include the lagged dependent variable MS_{imt-1}, several lags of RJV participation, $RJV_{imt-\tau}$, lags of the firm's R&D expenditures in logs, $Log(R\,\&\,D)_{imt-\tau}$, and X_{mt-1}, a vector of lagged industry-level control variables.[26] Finally, η_{im} is a firm-specific fixed effect, η_t is a time fixed effect, and ε_{imt} is an i.i.d. normally distributed error term.

Our control variables are defined in Table 1. Since market shares are persistent over time (Mueller, 1985; Gugler and Siebert, 2007), the market share equation is specified as an autoregressive process. By adding the lagged terms of a firm's market share, the RJV participation variable effectively captures deviations from a firm's market share trend.

To account for differences across firms' innovativeness and their impact on market shares, we incorporate R&D expenses at the firm level; see Hall, Mairesse and Mohnen (2010) for an overview of the returns of R&D. This idea goes back to Leonard's (1971) seminal study, which finds a positive correlation between R&D spending and sales growth. Several lags of firm-level R&D spending are included, given that its effect typically takes time to materialize (Mansfield, 1965; Pakes and Schankerman, 1984).

Finally, industry-specific factors are added.[27] In particular, given that we want to control for the differential impact of a firm's R&D spending relative to the industry in which it operates, we control for the lagged industry's average R&D expenditures (variable Log(*R&D)_Industry*). We further include a lagged term of the average

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[26] The parameter τ stands for the precise lag. In our main specification, we chose to include up to two lags of RJV participation, i.e. a contemporaneous effect ($\tau = 0$), plus two previous years ($\tau = 1$ and $\tau = 2$). This choice is dictated by the need to balance two effects: to account for sufficient time such that RJV participation can affect the market outcome and to drop as few time periods, and hence observations, as possible. For consistency, we use the same number of lags for our other firm-level variable, i.e. R&D expenditures. The inclusion of further lags for both variables does not significantly affect our results.

[27] We use one lag in this case to account for possible feedback effects and to reduce potential endogeneity issues. Given that these are industry control variables, the more complex and longer lag structure used for our main variables of interest is not replicated.

firm's market value (in logs) of the SIC4 industry in which the firms operates (Log(*MarketValue)_Industry*), which serves as well as time-varying industry fixed effect. [28]

There is the possibility that time-specific factors may influence a firm's market share. The equation therefore contains a full set of yearly time dummies which take into account time-specific factors that are exogenous and common to all industries. Finally, due to possible firm-specific time-invariant factors, we include firm fixed effects.

The estimation proceeds as follows. We begin by looking at research collaboration as the dummy "RJV any", which takes on the value of one whenever a firm is involved in at least one RJV, and the value of zero otherwise. We further distinguish between RJVs where firms do not meet direct competitors (vertical RJV) and those where they do (horizontal RJV); both are again defined as dummy variables. The focus then shifts to horizontal RJVs, explicitly taking the network structure into account, and dummies are constructed for our different size categories. This allows us to analyze heterogeneous effects of RJV participation and, hence, to make a more precise inference on the collusive potential of RJVs.

Econometric issues and identification

There are several econometric issues that need to be addressed. Since the unobserved panel-level effects are by construction correlated with the lagged dependent variables, the endogenous nature of lagged market shares must be accounted for to obtain a consistent estimator. The system GMM estimators developed by Arellano and Bover (1995) and Blundell and Bond (1998) are therefore used. These estimators, which have been widely adopted in the literature, use lags of levels and differences of the dependent and potentially endogenous or predetermined variables as instruments.[29] To correct for the downward bias of the system GMM two-step estimation of standard errors in a finite sample, we use the Windmeijer (2005) robust estimator.

[28] We experimented with different measures of size (total assets, sales, employees); results stay robust.

[29] While Arellano and Bond (1991) propose using moment equations coming from the conditions that lagged-levels of the dependent variable and the predetermined variables are uncorrelated with first-differences of the disturbances, Arellano and Bover (1995) and Blundell and Bond (1998) propose employing the additional moment conditions that lagged differences of the dependent variable are orthogonal to levels of the disturbances. To use these additional moment conditions, one needs to assume that panel-level effects are unrelated to the first observable first-difference of the dependent variable.

Moreover, there might be problems of endogeneity due to transitory shocks. The potentially biggest one is the fact that a temporary and unobserved firm-specific shock could simultaneously influence a firm's RJV participation and its market share. For example, it may be that RJV insiders are more successful in innovation and thus have a relatively larger market share. We use several strategies to mitigate this problem. First, we include several controls for this possible shock – time dummies, industry's average R&D and market value, firm fixed effects and, most importantly, firm-level R&D. [30]

Second, our system GMM estimator allows us to use an instrumental variable approach using both "internal" and "external" instruments. The internal instruments are essentially lags and lagged differences of the dependent variable, and our RJV participation and R&D measures. In terms of external instruments, the lagged firm's size (measured by total assets) is used, given Irwin and Klenow's (1996) findings that larger firms gain more from research cooperation and from R&D knowledge spillovers therein. More importantly, like Gugler and Siebert (2007), we include the lagged number of accumulated patents. A firm's lagged stock of patents is a measure of how efficiently it innovates and is thus a likely significant determinant of RJV participation, if firms (partly) join for innovation reasons. Indeed, as Cassiman and Veugelers (2002) show, firms better capture R&D spillovers from other participants when their innovative capacity is greater. The first two columns of the preliminary statistics in Table 2a show that firms participating in RJVs own a much higher patent stock (3.8 versus 150.9 discounted accumulated patents, respectively). Furthermore, firms in horizontal RJVs have more patents than insiders in vertical RJVs (167.9 versus 124.7 accumulated patents).

The lagged patent stock is a good instrument for RJV membership when it is correlated with RJV participation, controlling for the other factors that are used in the framework. Therefore, the research participation measures are regressed on the patent stock of firms, including the predetermined factors of our main regression.[31] Table 3

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[30] A firm's R&D may be suffering from similar problems. We correct for its potential endogeneity through the use of internal instruments available through the system GMM estimator.

[31] All the explanatory variables are lagged three periods to be sure that we do not infer correlations due to reverse causality and to mimic the instruments used in the main regression where lags 3 to 6 are employed as instruments. Results are qualitatively identical when using different lag structures.

shows that a firm's patent stock, indeed, significantly influences all types of RJV participation; the same holds for a firm's size, our other external instrument.[32]

[Insert Table 3 about here]

Furthermore, for patent stock to be a valid instrument, it must also be uncorrelated with the error term in equation (3). Thus, the exclusion restrictions are tested by estimating the firm's market share equation (3) as a function of its patent stock in all those industries where *no* RJVs are formed during the sample period –and thus also naturally excluding the RJV participation variable. If a firm's patent stock has no direct influence on its market share, then it must be the case that its impact in these industries is insignificant. As Table 4 shows for different lags of the patent stock, this turns out to be the case. Therefore, we are confident that lagged patent stocks are a good external instrument for research collaborations.[33]

[Insert Table 4 about here]

The final step of our empirical identification strategy is based on the role of heterogeneous effects. The theoretical setup predicts differential responses across distinct categories of RJV participation. If RJVs are (partly) used for collusive purposes, then our model predicts a positive impact on a firm's market share when

[32] Given that the GMM methodology is used, one can easily include more variables as instruments. Other candidates to account for a firm's participation are innovation measures, such as firm-level R&D expenditures. Table 2 grossly shows the same pattern for yearly R&D expenditures as was found for a firm's patent stock. Table 3 confirms that lagged firm-level R&D expenditures significantly influence the different dimensions of research collaboration. We therefore also employ lagged R&D expenditures in the instrument matrix. Note that, given that we incorporate a measure for a firm's size, the instrument matrix includes R&D expenditures and not R&D intensity (which yields insignificant coefficients when replacing expenditures in the estimations in Table 3).

[33] We explain here in detail our instrumenting strategy. The internal instruments for the differenced equation are lags 3 to 6 of the market share, RJV-participation measures, and the log of R&D expenses, while the external instruments are the three-year lagged patent stock, total assets, the one-year lagged industry average of the log of market value and R&D expenses, and the set of year dummies. The internal GMM-type instruments for the level equation are the three-year lagged market share and the log of R&D expenditures. In some specifications we slightly departed from this general structure if the Hansen-Sargan test of over-identifying restrictions rejected our original structure. In these instances we reduced the number of used lags. In general, we employed a parsimonious lag structure to avoid the well-known problem of model-overfit due to including too many instruments, which can lead to the failure of cleaning up the endogenous components of the problematic regressors (Windmeijer, 2005). As a rule of thumb, it is often suggested to keep the number of the instruments lower than the number of panels, which is always and abundantly the case in our estimation. We also experimented with different lag structures and results are qualitatively robust.

participating in vertical RJVs but a negative impact when entering a horizontal RJV. Further, if the size of the horizontal network matters for collusion, then different size categories might yield distinctive effects on a firm's market share. Since our empirical results generate different reactions for dissimilar types of RJV participation, this is further evidence that endogeneity has been addressed. Indeed, it is hard to come up with a story for why an omitted shock should yield other results for different categories. Although one can never fully rule out the possibility that some complex interaction of omitted shocks would drive the results, this seems unlikely.

5. Results

Specification tests and control variables

First, some specification tests are performed. For convergence, the point estimate of the lagged dependent variable needs to be less than 1. This test is performed for all specifications. We can never reject the null hypothesis that the coefficient is less than 1 (at the 1% or 5% significance level).

Two standard specification tests are applied on the system GMM estimator. First, since the number of instruments is much larger than the potentially endogenous variables, the Hansen-Sargan J statistic for over-identifying restrictions can be used to test for the joint exogeneity of the moment conditions. Second, to define the moment conditions, the system GMM hinges on having no serial correlation in the error terms. Given that our fixed effect estimator is based on first differences, one can check this assumption by testing the absence of second-order serial correlation in the disturbance term (Arellano and Bond, 1991). In all specifications, the Hansen-Sargan and the Arellano-Bond tests show that the estimation performs well: we cannot reject the joint hypothesis that the over-identifying restrictions are valid (i.e. our instruments are exogenous) and we reject the presence of autocorrelation.

The parameter estimates for the control variables are intuitive. Most importantly, R&D exerts a negative effect on MS, although this effect is weak.[34] Given that the focus of this paper is on the collusive intent underlying research

[34] In the RJV any-specification (column 1 of Table 5), the cumulative R&D effect is -0.0039 (p-value 0.11). In the RJV vertical vs. RJV horizontal specification (column 2) the cumulative R&D effect is -0.0008 (p-value 0.56). In the last specification, where we compare RJV vertical to the small-medium-large horizontal networks (column 3), the cumulative R&D effect is -0.0002 (p-value 0.16).

cooperation, the parameter estimates for the controls in further specifications and samples are not discussed, since their impact is similar across all regressions.

RJV participation – horizontal vs. vertical RJVs

We begin by testing whether any type of RJV participation yields a significant change in market shares. Given that we allow for the effect to work through several periods, for this and subsequent regressions only the cumulative effect of three subsequent years is reported. As can be seen in Table 5, the impact is negligible. A positive effect of less than 0.2 percentage points is found, and this gain in market share is not significant. This result is in line with Gugler and Siebert (2007), who discover a cumulative increase in market share of 0.52 percentage points in the US semiconductor industry. Given the likely heterogeneity in the incentives to participate in an RJV, this average result is not surprising. If some RJVs take place for innovative reasons, while others are started for collusive purposes, then the net effect may simply be inconsiderable across all cases.

[Insert Table 5 about here]

We therefore explore the characteristics of RJVs and check whether they are systematically related to collusion. Specifically, vertical and horizontal RJVs are separated. The second column of Table 5 reports the impact of vertical RJVs; membership therein increases a firm's market share with 3.4 percentage points, which is significant at the 5% level. That implies that RJVs among non-competitors yield significant efficiency gains and that collusion plays no role. This finding is in accordance with the fact that non-horizontal relationships typically have positive welfare effects. It is also consistent with our framework where RJVs that are set up purely for innovation should increase insiders' market share. The result therefore confirms our formal set-up. In addition, the higher market share appears to be linked to an increased level of R&D expenditures, indicating that research exhibits strategic complementarities, as explained in footnote 17.[35]

[35] In an OLS regression, which is not reported because of space constraints, we estimate the log of R&D expenses as a function of lagged participation in vertical RJVs, correcting for the other exogenous factors used in the main regression and using a full set of time dummies and firm fixed effects. The coefficient estimate of vertical RJV membership is positive and statistically significant at the 5% level.

As we are interested in collusion, we zoom further in on horizontal RJVs. We begin by estimating the *average* effect of horizontal RJVs using the dummy variable approach. As can be seen in the second column of Table 5, a small cumulative market share loss of -0.17 percentage points is detected, but the effect is statistically insignificant. This implies that for the *average* horizontal RJV, efficiencies and collusionary effects on market shares are statistically balanced. In terms of our framework, it also suggests that consumers do not benefit *on average* from horizontal RJVs. While this result is interesting in its own right, we further proceed by investigating the characteristics of horizontal RJVs.

RJV participation –network effects

We examine whether the total number of direct links with competitors plays any role. Using the dummy variables defined in Section 3, we test whether the size of the formed network is systematically related to collusion. Column 3 of Table 5 shows that small horizontal networks yield a small positive effect on market shares of 0.43 percentage points (although not significant), medium-size networks decrease the market share by -0.93 percentage points (significant at the 10% level), while firms in large networks show a -2.8 percentage point change (significant at the 5% level). These coefficients indicate that the larger the network, the bigger and the more significant the effect on market shares is. This shows that product market coordination is statistically related to large horizontal networks, while there is no evidence that small networks are prone to collusion.

To exclude the possibility that larger networks lead to a decrease in market share due to increased agency problems or higher coordination costs, we investigate the impact of size in vertical networks. Under the plausible assumption that these issues are similar in both vertical and horizontal RJVs, a positive effect of size on market shares in collaborations among non-competitors is inconsistent with efficiency losses in larger networks. As is shown in Table 6, medium-size and large vertical networks lead to a significant increase in market share of their participating firms.[36]

[36] Note that our vertical network is constructed in a slightly different way to our horizontal network. Given that one cannot easily come up with a relative measure for non-competitors, we just sum the unique contacts of a given firm in its vertical RJVs. We then look at the distribution of this count and divide vertical RJVs in small (the first quartile of the distribution), medium (the second and third quartile), and large (the top quartile).

This strongly suggests that the negative market shares in larger horizontal networks cannot be attributed to efficiency losses.

[Insert Table 6 about here]

In sum, the results confirm that large horizontal networks are prone to collusion in the product market. This contrasts with the results for vertical RJVs, which lead to innovative gains that are increasing with the size of the created network.

Besides having policy relevance, these findings also lend further support to our identification strategy, as it is hard to explain through an omitted shock how different types of RJVs and size classes of the formed networks would yield a differential outcome on a firm's market share.

Critical network size

In order to estimate a critical network size above which collusion can be identified, a continuous model is proposed. In particular, the following market share equation is estimated:

$$(4) \qquad MS_{imt} = \alpha_0 + \alpha_1 MS_{imt-1} + \sum_{\tau=0}^{2} \beta_{1\tau} RN_{imt-\tau} + \sum_{\tau=0}^{2} \beta_{2\tau} RN_{imt-\tau}^{2}$$
$$+ \sum_{\tau=0}^{2} \gamma_\tau Log(R\,\&\,D)_{imt-\tau} + \lambda X_{mt-1} + \eta_{im} + \eta_t + \varepsilon_{imt},$$

where all variables are as in equation (3), except that we define a new continuous horizontal network variable RN and further include its quadratic term RN^2. This quadratic specification can be associated with a specific parameterization of our general theoretical framework where demand is linear, competition is in quantities and firms face increasing marginal costs and/or differentiated products.[37]

Figure 2 plots the estimated continuous effect for the network variable from equation (4) and compares it to the discrete heterogeneous effect reported in column 3 of Table 5. The continuous specification traces out the categorical specification, i.e.

[37] This parameterization is equivalent to the classical merger paper by Perry and Porter (1985), which can be adapted to an RJV model where participation may lead to efficiency gains and/or product market collusion. See Banal-Estañol and Ottaviani (2006) for a full derivation of this framework. As a robustness check, we estimated the model with a polynomial of third degree. The results from this estimation are qualitatively identical to those obtained with our quadratic form in terms of point estimates. However, we lose precision, which points to possible specification problems with the cubic functional form and to the chosen quadratic form better fitting the data.

participating in small networks has a positive near-zero impact on market shares, while membership in larger networks yields a significantly negative effect. In particular, the plot follows a U-shaped pattern, which reaches a minimum at a network size of 0.69, where firms on average lose a market share of -3.8%.

[Insert Figure 2 about here]

Most importantly for our purposes, a critical network size K^* can be identified above which the market share of insiders is lower than that of outsiders. Specifically, we estimate this critical point to lie at $K^*=0.18$ (10% significance level). In other words, participation in horizontal RJVs, thereby leading to a network with direct competitors that consist of more than 18% of the firms in that market, is likely to lead to collusion.[38]

Empirically, we find that 29% of the observations that have a strictly positive value for the horizontal network variable fall above that critical threshold. This corresponds to 198 out of 678 unique firms which at any time participated in horizontal RJVs.

One can make use of the estimated critical value to indicate some industries in which firms' RJV membership leads to horizontal networks above the threshold. Suspect combinations come, for example, from small networks (of three firms) in a small industry of nine firms, resulting in a relative network size of 0.33 ("Soap, Detergents, Perfumes and Cosmetics", SIC=2840). At the other end of the spectrum, the "Special Industry Machinery" (SIC=3559) has the most links in absolute terms counting 21 firms (covering 0.38 of the industry). In relative terms, the largest network is situated in the Electronic Computers industry (SIC=3571), where 47% of the competitors are connected via RJVs (16 out of 34 firms in the industry). Table 7 shows these and more industries that are suspect under our framework.

[Insert Table 7 about here]

[38] Given the low frequency of high values for the horizontal network variable (see also Figure 1), we lose some precision in the network coefficients' estimates when we are approaching the end of the distribution. Less than 2 % of the values for the network variable lay above the threshold of 0.7, which makes confidence intervals widen substantially. These observations can be traced back to 7 firms that all belong to the cement and hydraulic industry (SIC4=3241).

An alternative measure for horizontal networks is further constructed, which counts not only a firm's direct but also its indirect links. This accounts for the possibility that firms can potentially collaborate in collusion via indirect contacts, for instance through a "central player" that communicates with "fringe players" to coordinate on collusion, even when these fringe players are not directly connected. It is shown in the Appendix that this network variable yields virtually the same results on firms' market shares.

6. Conclusion and Implications

Given the pressing need for economies to innovate, governments often encourage firms to cooperate in R&D since collaborations may help firms to obtain research objectives more efficiently. However, joint activities that create networks among competitors may also facilitate collusion in the product market, which is socially undesirable.

This paper investigates whether RJVs lead to coordination in the product market. In particular, we derive an empirically tractable identification condition that allows us to test whether collusion has taken place. A decline in market shares of firms participating in RJVs is a necessary condition for collusion and, at the same time, is necessary and sufficient for consumer surplus to decrease. This approach is applied to data on R&D collaborations created under the National Cooperation Research Act (NCRA), which was established to stimulate joint research by granting antitrust exemptions.

The main findings are summarized as follows. No *average* effect of RJVs on market shares is found. As a result, one cannot identify product market collusion for all RJVs. By contrast, RJVs where direct competitors meet (horizontal RJVs) are more suspect than RJVs between non-competitors (vertical RJVs). Moreover, we find that the size of the created inter-firm network through membership in several RJVs is an important driver. Our results show that large horizontal networks are most prone to collusion in the product market. This contrasts with the results for vertical RJVs, which lead to efficiency gains that are increasing with the size of the vertical network.

Specifically, we estimate the critical size above which our test identifies collusion. This occurs when the formed network includes more than 18% of direct competitors. Empirically, 29% of our sample with a strictly positive horizontal network value falls above that critical threshold. This corresponds to 198 out of 678 unique firms which at any time participated in horizontal RJVs.

In terms of policy, this finding is rather worrisome as it suggests that a large number of firms create networks that are above the identified critical point, thereby enabling collusion in the product market and leading to a reduction in consumer surplus. The results of this paper, therefore, have some significant implications for competition policy vis-à-vis research cooperations. First, the likelihood of collusion in the product market is significant and depends on the type and the size of the created network. This suggests that a *per se* approach to RJVs is unlikely to lead to an efficient enforcement regime. In particular, our findings suggest that an *effects-based* approach for large horizontal networks created through RJV-participation is appropriate.

Second, even those RJVs that are below the critical network size *may* lead to collusion in the product market. In this case, the efficiencies are large enough to compensate any possible collusive effects in terms of market share, so that consumers are better off. From the welfare perspective, these RJVs would in principle not be problematic since the standard in antitrust – in the US as well as Europe – is consumer surplus. However, collusion is a hard-core violation and thus illegal *per se*. In that sense, competition policy may have a challenge here from the legal perspective to the extent that product market collusion and R&D efficiencies may both occur, leading the *net* effect on consumers to be positive.

In terms of future research, a natural next step of this approach would be to investigate how the intensity of RJV-links influences the likelihood of collusion. Some firms meet each other several times across different RJVs, which clearly further facilitates possibilities to coordinate on product market cooperation.

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Appendix: Industry-Wide Network Variable

We construct an alternative measure of research networks, based on both direct and indirect links among competitors. In particular, we propose a network variable which represents the percentage of firms in a given industry involved in at least one horizontal RJV. This measure thus accounts for the possibility that firms can also potentially collaborate towards collusion via indirect contacts. As such, it can be seen as a network definition that lies at the other end of the spectrum. Indeed, whereas our main network variable counts only direct links –and is thus the most narrow– the proposed network measure in this section is the broadest possible. Clearly, if many firms in an industry are directly linked, i.e. when the network is dense, then our two measures should coincide. As can be seen from Figure 3, the new distribution is shown to be similar to our initial network variable, although less skewed to the left; see also the values for the variable "coverage" in Tables 1, 2a and 2b.

[Insert Figure 3 about here]

We estimate the same equation as in (3), but using this alternative network variable. The results obtained are very much in line with our main findings (see Figure 4); the critical network size above which market shares of participating firms are significantly negative can be found at $K^{**}=0.16$.

[Insert Figure 4 about here]

Tables and Figures

Table 1: Variable definitions

Variable	Definition
Market share (MS_{imt})	Firm i's market share in its primary SIC4 industry in a given year *t*. The market share for firm *i* in industry *m* at time *t* is $MS_{imt} = (total\ sales_{imt} - foreign\ sales_{imt}) / \sum_{i=1}^{N_{mt}} (total\ sales_{imt} - foreign\ sales_{imt})$, where N_m is the number of firms in industry *m*. All sales are in million US \$.
RJV Any_{imt}	Dummy equal to 1 if firm *i* participates in at least one RJV at year *t*.
RJV $Vertical_{imt}$	Dummy equal to 1 if firm *i* participates in at least one RJV at year *t*, but it does not meet any competitor, where competitor is defined as a firm with the same primary SIC4.
RJV $Horizontal_{imt}$	Dummy equal to 1 if firm *i* participates in at least one RJV with at least one competitor at year *t*, where competitor is defined as a firm with the same primary SIC4.
Total $Assets_{it}$	Firm *i*'s total assets in year *t*, in million US \$.
$R\&D_{it}$	Firm *i*'s yearly R&D expenses, in million US \$.
Patent $stock_{it}$	Firm *i*'s cumulated patents at year *t*, calculated as Patent $stock_{it}$ = (1-0.15) Patent stock $_{it-1}$ + Patents $application_{it}$ (see e.g. Hall, 1990, and Griliches and Mairesse, 1984).
Network (RN_{imt})	Number of links with SIC4 competitors through RJV participation, over the total number of possible links in the same SIC4.
$Coverage_{mt}$	Percentage of the firms in the same SIC4 industry which are connected via RJV participation.
R&D_$Industry_{mt}$	Industry average yearly R&D expenditures at the SIC4 level, in million US \$.
MarketValue_$Industry_{mt}$	Average yearly market value at the SIC4 level, in million US \$.

Table 2a: Preliminary statistics for different categories of RJV participants versus non-participants

	No RJV		Any RJV		Vertical RJV		Horizontal RJV	
Variable	mean	sd	mean	sd	mean	sd	mean	sd
Market Share	0.0730	0.1557	0.1491	0.2182	0.2268	0.2643	0.0984	0.1630
Total Assets	1,119.0000	9,337.2140	8,688.5660	29,988.5100	6825,3960	24,392.0400	9,908.0010	33,090.1700
R&D Expenditures	2.5932	32.0338	144.1250	548.0336	70,5578	234.1988	192.1945	674.5062
Patent stock	3.8045	85.3941	150.8789	523.1952	124,7769	422.3369	167.9342	579.1164
# Horiz. RJVs	-	-	2.6053	8.3426	-	-	4.0273	10.2926
Horizontal Network	-	-	-	-	-	-	0.1478	0.1839
Coverage	-	-	-	-	-	-	0.1781	0.1388
Obs.	59,996		5,987		2,366		3,621	

Table 2b: Preliminary statistics for horizontal networks in different size classes

	Small		Medium-sized		Large	
Variable	mean	sd	mean	sd	mean	sd
Market Share	0.0432	0.0988	0.0950	0.1540	0.1604	0.2056
Total Assets	13,014.5500	45,145.3700	5,260.0830	10,280.2500	16,100.7300	45,206.5600
R&D Expenditures	97.8843	291.1504	145.7234	522.6698	379.4984	1,068.5290
Patent stock	92.5980	303.9908	170.6768	651.2230	237.7822	625.1998
# Horiz. RJVs	1.6674	2.1588	2.7189	4.5967	9.0055	18.5320
Horizontal Network	0.0174	0.0080	0.0918	0.0468	0.3900	0.2213
Coverage	0.0958	0.0631	0.1499	0.0833	0.3166	0.1781
Obs.	905		1,811		905	

Table 3: Instruments for RJV participation

Dependent Variable	Any RJV	Vertical RJV	Horizontal RJV	Horizontal Network-Small	Horizontal Network-Med.	Horizontal Network– Large
Estimation Method	Probit	Probit	Probit	Probit	Probit	Probit
Patent $stock_{t-3}$	0.0040***	-0.0005**	0.0016**	0.0015***	0.0016**	0.0022***
	(0.0007)	(0.0003)	(0.0006)	(0.0005)	(0.0007)	(0.0006)
Log(Total $Assets)_{t-3}$	0.520***	0.179***	0.477***	0.269***	0.404***	0.493***
	(0.0471)	(0.0315)	(0.0470)	(0.0433)	(0.0369)	(0.0838)
$Log(R\&D)_{t-3}$	0.457***	0.202***	0.375***	0.339***	0.400***	0.675***
	(0.0532)	(0.0470)	(0.0469)	(0.0659)	(0.0500)	(0.110)
Log(R&D)_$Industry_{t-1}$	0.958***	0.197**	0.867***	0.148	0.610***	1.440***
	(0.111)	(0.0847)	(0.111)	(0.120)	(0.0960)	(0.196)
Log(MarketValue)_$Industry_{t-1}$	-0.106*	-0.111**	-0.150***	-0.494***	-0.0687	0.296**
	(0.0600)	(0.0563)	(0.0572)	(0.0901)	(0.0617)	(0.122)
Constant	-9.758***	-6.136***	-8.290***	2.318***	2.329***	3.310***
	(0.411)	(0.264)	(0.410)	(0.0430)	(0.0410)	(0.0512)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	30,419	30,419	28,577	29,389	28,676	28,676

We show regressions for all our RJV participation measures. We use a panel probit estimation methodology given the dichotomous nature of our participation variables (any RJV, vertical RJV, horizontal RJV, small horizontal network, medium horizontal network, and large horizontal network). In all specifications we control for the other exogenous regressors from our main specification and add firm random effects and year dummies.

Table 4: Effect of patent stock on firms' market shares in industries with no RJVs

Dependent Variable	MS	MS	MS
Estimation Method	System GMM	System GMM	System GMM
MS_{t-1}	0.9610***	0.9622***	0.9631***
	(0.0309)	(0.0308)	(0.0307)
Patent $stock_{t-1}$	0.00004		
	(0.00008)		
Patent $stock_{t-2}$		0.00006	
		(0.00008)	
Patent $stock_{t-3}$			0.00008
			(0.00009)
Cumul. Log(R&D) effect	-0.0237**	-0.0243**	-0.0247**
	(0.0100)	(0.0100)	(0.0100)
Log(Market Value)_$Industry_{t-1}$	0.0004	0.0004	0.0004
	(0.0014)	(0.0014)	(0.0014)
Log(R&D)_$Industry_{t-1}$	0.0335***	0.0340***	0.0344***
	(0.0119)	(0.0117)	(0.0116)
Constant	-0.0003	-0.0006	-0.0008
	(0.0051)	(0.0051)	(0.0052)
Sargan test (Prob > chi2)	0.1247	0.136	0.1435
	(57)	(57)	(57)
Arellano-Bond test (Prob > z)	0.761	0.7666	0.7696
Obs.	43,600	43,600	43,600

We report System GMM estimates of the market share equation in the sample of industries with no RJVs. MS, and Log(R&D expenses) are treated as endogenous. For space reasons, only the cumulative effects of Log(R&D) are reported, which represents the sum of the effects from time *t* to time *t-2*. Windmeijer robust standard errors corrected for heteroscedasticity are stated in parentheses. We report the p-value of the Hansen-Sargan J test, where the degrees of freedom are in parentheses, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Table 5: RJV participation on market shares

	RJV any	Horiz. vs. Vertical	Horizontal Network
Dependent Variable	MS	MS	MS
Estimation Method	System GMM	System GMM	System GMM
MS $_{t-1}$	0.951***	0.914***	0.913***
	(0.0315)	(0.0506)	(0.0595)
Cumul. RJV effect - Any	0.00185		
	(0.0058)		
Cumul. RJV effect - Vertical		0.0337**	0.0467**
		(0.0198)	(0.0297)
Cumul. RJV effect - Horizontal		-0.0017	
		(0.0057)	
Cumul. Netw. effect – Horiz. -Small			0.0043
			(0.0078)
Cumul. Netw. effect - Horiz. -Medium			-0.0093*
			(0.0054)
Cumul. Netw. effect - Horiz. -Large			-0.0282**
			(0.0135)
Cumul. Log(R&D) effect	-0.0039	-0.0008	-0.0002
	(0.0025)	(0.0013)	(0.0002)
Log(Market Value)_Industry$_{t-1}$	0.0003	0.0003	-0.0003
	(0.0005)	(0.0005)	(0.0004)
Log(R&D)_Industry$_{t-1}$	0.0020	0.0027	0.0027
	(0.0023)	(0.0030)	(0.0023)
Constant	-0.0023	-0.0020	0.0006
	(0.0024)	(0.0029)	(0.0026)
Hansen-Sargan J test (Prob > chi2)	0.6781	0.7839	0.5609
	(116)	(123)	(233)
Arellano-Bond test (Prob > z)	0.9299	0.6829	0.5609
Obs.	36,593	36,593	36,593

We report System GMM estimates of equation (3). MS, RJV participation variables, and Log(R&D) are treated as endogenous. For space reasons, only cumulative effects of RJV participation and Log(R&D) are reported, which represent the sum of the effects from time *t* to time *t-2*. Windmeijer robust standard errors corrected for heteroscedasticity are stated in parentheses. We report the p-value of the Hansen-Sargan J test, where the degrees of freedom are in parentheses, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Table 6: Vertical networks on market shares

Dep. Var. Estimation Method	MS System GMM
MS_{t-1}	0.903***
	(0.0531)
Cumul. RJV effect - Horizontal	-0.00522
	(0.00562)
Cumul. Netw. effect – Vertical - small	-0.0015
	(0.0151)
Cumul. Netw. effect - Vertical - medium	0.0460**
	(0.0228)
Cumul. Netw. effect - Vertical - large	0.0368*
	0.(0210)
Cumul. log(R&D) effect	-0.0011
	(0.0011)
Log(Market Value)_Industry$_{t-1}$	0.0003
	(0.0004)
Log(R&D)_Industry$_{t-1}$	0.0024
	(0.0024)
Constant	-0.0023
	(0.0024)
Hansen-Sargan J test (Prob > chi2)	0.8084
	(159)
Arellano-Bond test (Prob > z)	0.8289
Obs.	36,563

We report System GMM estimates of equation (3) where we differentiate the effect of vertical RJVs depending on their size. MS, RJV participation variables, and Log(R&D) are treated as endogenous. For space reasons, only cumulative effects of RJV participation and Log(R&D) are reported, which represent the sum of the effects from time *t* to time *t-2*. Windmeijer robust standard errors corrected for heteroscedasticity are stated in parentheses. We report the p-value of the Hansen-Sargan J test, where the degrees of freedom are in parentheses, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Table 7: Critical network size and welfare assessment

SIC4	Industry Description	Year	% Firms above K*	# Firms above K*	# Firms in industry
2840	Soap, Detergents, Perfumes, Cosmetics	1999	0.3333	3	9
2911	Petroleum Refining	1999	0.1875	6	32
3312	Steel Works, Blast Furnaces (including Coke Ovens), and Rolling Mills	1998	0.2188	7	32
3510	Engines and Turbines	1996	0.4286	3	7
3559	Special Industry Machinery	1999	0.3818	21	55
3571	Electronic Computers	1991	0.4706	16	34
3572	Computer Storage Devices	1997	0.2059	7	34
3576	Computer Communications Equipment	1996	0.1944	14	72
4011	Railroads, Line-Haul Operating	1994	0.2174	5	23
4841	Cable and Other Pay Television Services	1992	0.2286	8	35

The variable *% Firms above K** represents the percentage of firms in a given industry/year that participate in horizontal RJVs and reach a network size larger than K*. The variable *# Firms above K** represents the number of firms that form a horizontal network larger than *K**. The variable *# Firms in industry* represents the number of firms in a given industry/year.

Figure 1: Size distribution of horizontal networks

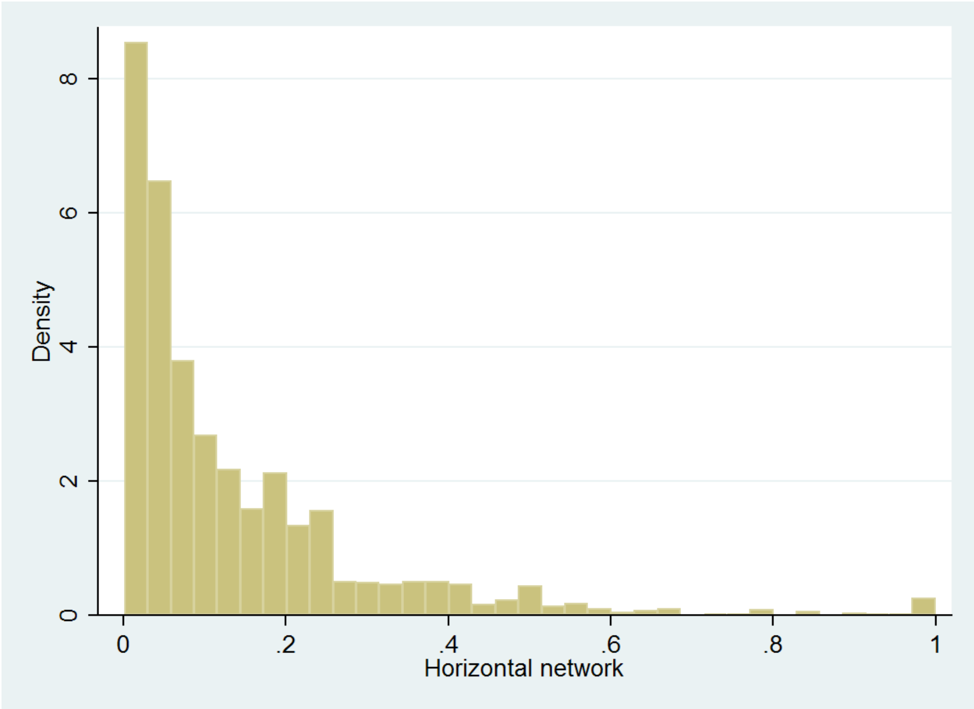

Figure 2: Market share impact of participation in horizontal networks: Discrete (three size classes) and Continuous Effects

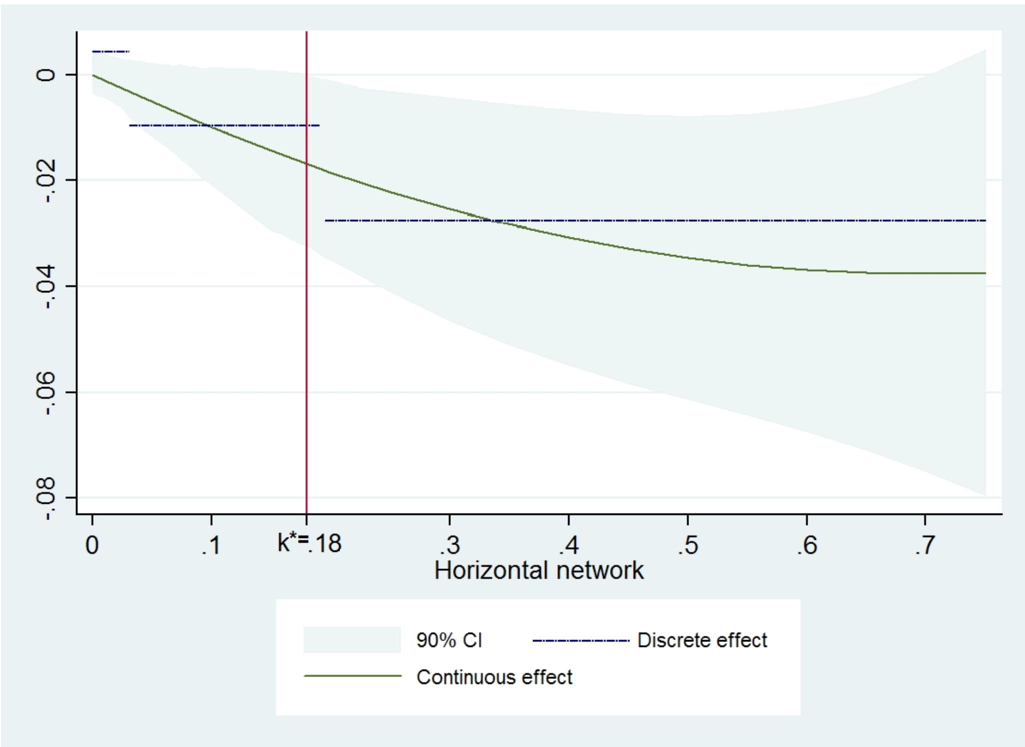

Figure 3: Size distribution of industry-wide networks

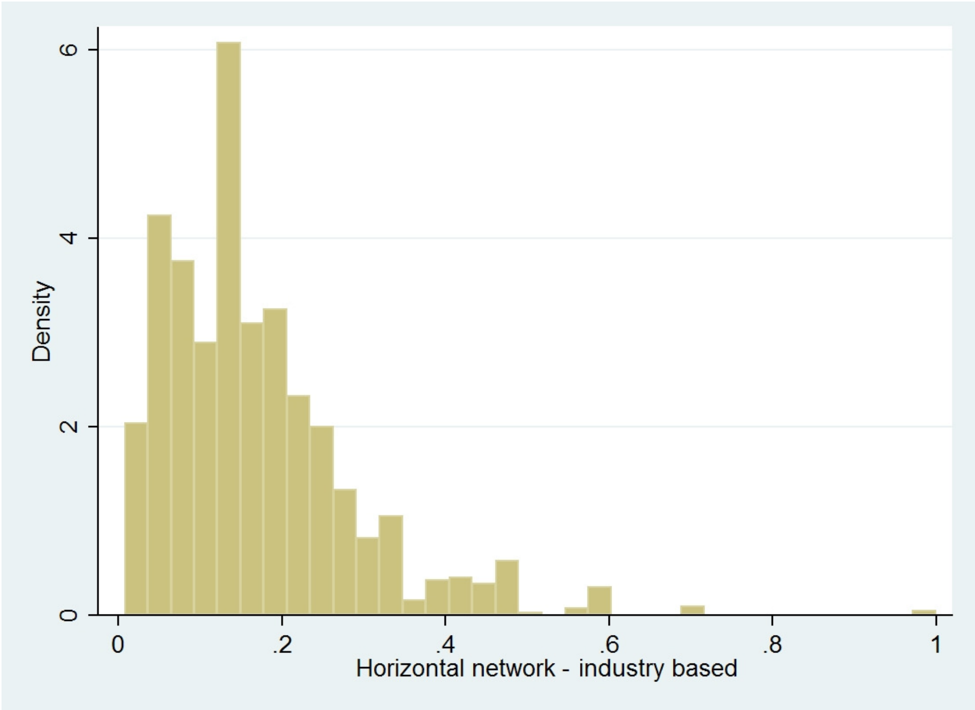

Figure 4: Market share impact of of participation in horizontal networks, Industry-wide network variable