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 U.S. 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.

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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 U.S. National Cooperation Research Act (NCRA). The NCRA was introduced in 1984 to raise U.S. competitiveness, in particular vis-à-vis Japanese firms. U.S. 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

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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 U.S. policy makers to include as many competitors as possible in the NCRA collaborations.

[4] For instance, in 1990 U.S. 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 Goeree and Helland (2010) for a discussion of this case.

at the R&D stage does not lead to coordination in the product market (Brander and Spencer 1983; Spence 1984; Katz, 1986; Kamien, Muller and Zang, 1992).[5] More recent contributions, however, show that RJV participation helps in sustaining collusion when firms are allowed to cooperate in the product market. 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

[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.

RJVs via market shares is that one does not need data on prices, costs, and elasticities, which are frequently not available, not reliable, or are difficult to measure.

There are few empirical studies on the relationship between R&D cooperation and market power. 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. Furthermore, Goeree and Helland (2010) investigate whether a toughening of the U.S. 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 after the introduction of the new policy, they conclude that the NCRA-program has led to collusion. Finally, Oxley, Sampson and Silverman (2009), through an event study, examine how RJV announcements in U.S. industries affect the stock market's evaluation of these firms' rivals. Their results also provide evidence in line with some RJVs being suspect of collusion.[7]

Our approach differs from the above works by relying on market shares, while also explicitly considering the heterogeneous effects of RJV participation. Specifically, we distinguish between RJVs among 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 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 among direct competitors that in some

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

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 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.

We further evidence that our findings are robust to different specifications of a firm's business and its direct competitors. In particular, while our main analysis assumes that firms dedicate resources, take strategic (collusion) decisions and identify rivals mainly in their most important industry, we show that the same results hold when taking the opposite view, i.e., assuming that firms operate through independent divisions in all business segments where they are present. Our results, therefore, hold for both a grouped and a divisional approach of a firm. Furthermore, we show that relatively larger firms are both more prone to participate in large horizontal networks and lose relatively more market share, tentatively indicating that larger firms cause relatively more collusive harm through their RJV participation. Finally, because of the importance of rightly capturing market shares in our analysis, we show that our measures are comparable to those of several other datasets.

The setup of the paper is as follows. The next section introduces the formal framework, where our theoretical identification strategy is presented. Section 3

[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; 16 competitors are connected in the computer industry and 21 in the special-industry-machinery sector.

describes the data and characterizes the network formation through RJV participation. Section 4 develops the empirical estimation strategy, and Section 5 explains the results. Section 6 shows several extensions and robustness checks. Finally, Section 7 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.

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 homogeneous 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. We show in an Appendix that, when imposing two standard conditions on the Cournot equilibrium to ensure uniqueness, one can characterize how aggregate output in this market, dX, moves in response to an (exogenous) change of output by a group of $K<N$ firms, dX_K:[11]

[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.
[11] The proof in the Appendix is a straightforward extension of Farrell and Shapiro (1990).

Lemma 1: *When firms compete à la Cournot, then an exogenous output change by a group of K<N firms, dX_K, moves aggregate output dX in the same direction, but by les,* $0 < \frac{dX}{dX_K} < 1$.

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 $c_{RJV}(x_i) \leq c_x(x_i)$ 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 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.[14]

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*

[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.

[14] Firms may have a preference to stay outside a purely collusive RJV; see e.g., Salant et al. (1983) where collusion is unprofitable unless 80% of the firms in the industry are involved. This result crucially hinges, however, on the assumptions of their model. One of their most restrictive assumptions – and one that is not needed in our more general setup– is the fact that demand is linear. If one relaxes this assumption, one can show that the profitability of joining a collusive group depends on the degree of concavity of demand. In particular, the less concave the demand the more profitable collusion becomes (Cheung, 1992; Fauli-Oller, 1997).

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.[15] 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

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

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 sufficient 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.*

This means that our identification strategy based on market shares can detect some but not all firms colluding through RJV participation. In particular, we can only detect those colluding firms that do not innovate "too much", where too much is defined by condition (1) above. Only when this occurs does the product market price also rises, leading to a decrease in consumer welfare.

[15] 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 homogeneous 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 among 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.[16]

[16] 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

Also, we do not characterize equilibrium situations. In other words, we are silent about the "coalition formation game" that is being played and only characterize some properties (market shares and prices) of possible outcomes.[17] If one would fully model this game and solve for its equilibria, then several outcomes are possible, depending on how one models the RJV formation game; see Bloch (1997) for a general overview of applicable coalition formation models, appropriate solution concepts and corresponding equilibria.

We now briefly explain the reasoning of why our identification condition also holds when firms compete in prices and products are differentiated.[18] Assume 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 the 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

outsiders. These results, therefore, indicate that a more elaborated RJV setup than ours would yield the same empirical identification.

[17] A "coalition" in our context is defined as a group of firms that in an RJV coordinate on collusion and/or innovation.

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

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% (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 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 are 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 Industrials database containing firm-specific information on about 22,000 publicly traded U.S. firms (1986–1999), and the NBER U.S. 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).[19] 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 U.S. In particular, the act allows American firms to establish large RJVs that conduct pre-competitive R&D and has been implemented by the U.S. Congress as part of an industrial policy to improve

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

international competitiveness of American companies and industries.[20] Under the terms of the NCRA, a notice must be filed with both the U.S. 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 Industrials database. The dropped firms are mostly small and, in a few cases, non-U.S. firms. The remaining companies constitute our sample of RJV participants. We then tie 630 out of the 1,013 entities to the NBER U.S. Patent Citations Data File, containing all filed U.S. 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 the lagged patent stock is one of the tools in our strategy to instrument for research collaboration and R&D investments (see e.g., Gugler and Siebert, 2007).

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. 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 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 firm-observations for which we have missing values on sales, as this variable is needed to define a firm's market share.

[20] 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)

Finally, those industries where the number of firms is lower than 3 are dropped as these are considered to be outliers.[21] The final sample, i.e., the included firms over the period 1986–1999, is an unbalanced panel with on average 428 insider-year observations (ranging from 128 in 1986 to 730 in 1999) and 5,431 outsider-year observations (ranging from 4,098 in 1986 to 6,761 in 1999).

The variables "market share" and "research collaboration" are the two fundamental variables in our empirical analysis, and are therefore first discussed. Market shares are constructed by using firms' sales in their primary 4-digit standard industry classification (SIC4), as reported by the COMPUSTAT North America Industrials database. [22] This SIC aggregation level is equivalent to the currently used 6-digit NAICS level and 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 relevant antitrust market is smaller.[23] 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.

Given the importance of market shares for our analysis and, hence, also the database from which we construct these measures, it is opportune to discuss this matter in more detail. An important reason why we employ the COMPUSTAT North America Industrials database is because other recent studies on RJV participation and collusion use exactly this same dataset. Indeed, Goeree and Helland (2010) use firm-level information from the North America Industrials database to construct, among other variables, market shares and measures of market power. Oxley et al. (2009) apply this database to define a firm's rivals and to construct concentration indices. By employing the same data across different papers, the studies and their results become more comparable. However, to convince the reader that the COMPUSTAT Industrials database itself is appropriate for our analysis, we extensively show the robustness of our results in Section 6 and comment upon the suitability of this dataset.

[21] There exists a COMPUTAT SIC4 code 9997 "Industrial Conglomerates" that includes six firms. Of course, conglomerates should not be included in our dataset, since code 9997 does not constitute a real industry. We, therefore, also exclude these six conglomerates from our analysis.

[22] 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).

[23] 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, Neven and Roeller (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.

As to RJV participation, our first measure 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 equal to one 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 that firm does not meet any competitor in any RJV where it is present.

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.[24] 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 into 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 a particular RJV. 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 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

[24] 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).

Harrington (2010) and Escrihuela-Villar (2008) indicate, although partial collusive networks are stable, they need to be large enough to be profitable. 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 turns 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 of 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.[25] Therefore, the relative size of firm *i*'s horizontal research network in an industry *m* in year *t* is defined as

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

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

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

.

[25] For completeness, we further in the paper re-do our analysis with (i) a network measure that also takes into account indirect links between firms (see footnote 39), and (ii) a network measure that takes into account participating firms' market shares (see Section 6).

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 $Horizontal\ \ Net_{imt} \in [0,1]$.[26]

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 met 9 of its 31 competitors through participation in several RJVs (the horizontal network size is therefore 0.29), while it linked with only 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 met 22 out of 127 firms in several horizontal RJVs, thereby creating a horizontal network of 0.173, whereas it only met 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

[26] 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%.[27]

[Insert Figure 1 about here]

Taking a first look at how network size matters, the same regularities emerge for both our network measures. 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 the 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).

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

Our test is implemented by estimating a 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:

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

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, $Log(R\,\&\,D)_{it-\tau}$, and X_{mt-1}, a vector of lagged industry-level control variables.[28] Finally, η_i 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).

[28] 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.

Finally, industry-specific factors are added.[29] 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 (Log(*R&D)_Industry*). We further include a lagged term of the average 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 effect.[30]

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 measured by 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 the 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 consistent estimates. 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.[31]

[29] 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.

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

[31] 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-

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.

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. Also R&D expenditures may suffer from the same problem. 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.

Second, our system GMM estimator allows us to use an instrumental variable approach using both "internal" and "external" instruments. Indeed, GMM estimators are not only useful for avoiding dynamic panel bias. The flexible framework of GMM can accommodate multiple endogenous variables and GMM estimators can be regarded as providing implicit models for the optimal instruments (Arellano, 2003). Our internal instruments are essentially lags and lagged differences of the dependent variable, and our (potentially endogenous) 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. Furthermore, like Gugler and Siebert (2007), we include the lagged number of accumulated patents. In both cases, we invoke the identification condition that the lagged values of these variables are uncorrelated with the error term. 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).

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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 the condition that panel-level effects are unrelated to the first observable first-difference of the dependent variable. We later show that this is indeed the case in our framework.

Furthermore, firms in horizontal RJVs have more patents than insiders in vertical RJVs (167.9 versus 124.8 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 lagged patent stock of firms, including the predetermined factors of our main regression.[32] Table 3 shows that a firm's patent stock, indeed, significantly influences all types of RJV participation; the same holds for lagged firm size and lagged R&D expenditures.[33] Furthermore, for all our measures to be valid instruments, they must be uncorrelated with the error term in equation (4). Their correlation with the residuals is indeed close to zero as will be explained in more detail in the next section, confirming that we have workable instruments in our setting.

It is important to note at this stage, however, that while the system GMM estimator is a useful tool to deal with endogeneity, an underappreciated problem often arises in its application. The GMM methodology may lead to an asymptotic bias when some of the explanatory variables are endogenous (Arrellano, 2003) and could overfit the endogenous variables when abusing of instrument proliferation (Roodman, 2009). In other words, having too many instruments can lead to a failure to clean up the endogenous components of the potentially problematic regressors (Windmeijer, 2005). We will argue in the section on results that this is not the case in our estimations.

[Insert Table 3 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 participating in vertical RJVs but a negative impact when entering a horizontal RJV.

[32] 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.

[33] 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).

Further, if the size of the horizontal network matters for collusion, then different size categories might yield a distinctive effect 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

First, some specification tests are performed. For convergence, the point estimate of the lagged dependent variable needs to be less than 1. Unit root tests indeed indicate that the market share data-generating process is stationary. In particular, we perform for all specifications unit-root Fisher type tests, which are suitable for unbalanced panel data like ours. All results strongly reject the null hypothesis that the panels contain unit roots (at the 1% significance level).

Several test statistics are then applied to the system GMM estimator. First, since the number of instruments is much larger than the potentially endogenous variables, the Sargan statistic for over-identifying restrictions can be used to test for the joint exogeneity of the moment conditions. As Tables 4 and 5 show, for all our estimations we cannot reject the joint hypothesis that the over-identifying restrictions are valid. Our instruments as a whole are thus not correlated with the residuals. We furthermore applied difference-in-Sargan tests to verify exogeneity for several subsets of instruments.[34] For different subsets, we cannot reject the null hypothesis of no correlation, thereby giving further validity to our choice of instruments.

Second, to use the additional moment conditions of the system GMM that extends the original Arellano-Bond estimator in differences, one needs the condition that the lagged first difference of the dependent variable is uncorrelated with the

[34] A difference-in-Sargan test checks the validity of a subset of instruments. This is done by computing the increase in the test statistic when the given subset is added to the estimation set-up. Under the same null of joint validity of all instruments, the change in the test statistic is χ^2 distributed, with degrees of freedom equal to the number of added instruments.

current unexplained change in the dependent variable (i.e., the error term). One can check this condition by applying a difference-in-Sargan test to all the GMM instruments for the levels equation (Blundell and Bond, 1998). We cannot reject the null hypothesis of no correlation at usual levels of significance for all our specifications (see Tables 4 and 5). These tests, thus, give support to the applicability of the system GMM estimator in our setting.

Third, 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 Arellano-Bond tests show that the estimation performs well: we reject the presence of autocorrelation.

Finally, an asymptotic bias of GMM estimators could be a problem. Arrellano (2003) shows that this bias is of order T/N in the case of endogenous variables, where T is the number of periods and N the number of groups. Given our particularly large number of groups ($N=5,785$) and relatively low number of periods ($T=12$), this seems not to be an issue in our analysis. Related to this problem, a too large instrument collection with the system GMM estimator may overfit potentially endogenous variables, given that the number of instruments grows exponentially with the number of periods if one includes all available lags in the instrumental matrix (Arellano, 2003; Roodman, 2009). We therefore limit the number of lags in all specifications when we build our instruments. As a result, the amount of instruments in our setting is only linearly related to T. We consequently employ a small number of instruments relative to the number of groups and thus comply with "good practice" of the system GMM as advocated in Roodman (2009).[35]

[35] We explain here in detail our instrumenting strategy. The internal instruments for the differenced equation are lags 2 to 5 of the market shares and the log of R&D expenses, and lag 3 of RJV participation. 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 departed slightly from this general structure if the Sargan test of over-identifying restrictions rejected our original structure. In these instances we reduced the number of used lags. We also experimented with different lag structures and results are qualitatively robust.

Control variables

The parameter estimates for the control variables are intuitive. Most importantly, R&D exerts in general a positive effect on MS, although this effect is weak. Given that the focus of this paper is on the collusive intent underlying research 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 4, the impact is negligible. A negative effect of about -0.24 percentage points is found, and this loss in market share is not significant. 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 4 about here]

We therefore explore the characteristics of RJVs and check whether they are systematically related to collusion. Specifically, we distinguish between vertical and horizontal RJVs. The second column of Table 4 reports the impact of vertical RJVs; membership therein increases a firm’s market share with 4.8 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 16.[36]

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 4, a small cumulative market share loss of -0.91 percentage points is detected, but the effect is statistically insignificant. This implies that for the average horizontal RJV, efficiencies and collusion 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 4 shows that small horizontal networks yield a small negative effect on market shares of 0.95 percentage points (although not significant), medium-size networks decrease the market share by -1.37 percentage points (significant at the 10% level), while firms in large networks show a -2.65 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 network 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 5, medium-size and large

[36] 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 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.

vertical networks lead to a significant increase in market share of their participating firms.[37] This strongly suggests that the negative market shares in larger horizontal networks cannot be attributed to efficiency losses.

[Insert Table 5 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:

$$(5) \qquad MS_{imt} = \alpha_0 + \alpha_1 MS_{imt-1} + \sum_{\tau=0}^{2} \beta_{1\tau} RN_{imt-\tau} + \sum_{\tau=0}^{2} \beta_{2\tau} RN_{imt-\tau}^{2} + \sum_{\tau=0}^{2} \gamma_\tau Log(R\,\&\,D)_{it-\tau} + \lambda X_{mt-1} + \eta_{im} + \eta_t + \varepsilon_{imt},$$

where all variables are as in equation (4), 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.[38]

[37] 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).

[38] 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

Figure 2 plots the estimated continuous effect for the network variable from equation (5) and compares it to the discrete heterogeneous effect reported in column 3 of Table 4. The continuous specification traces out the categorical specification, i.e., participating in small networks has a 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 0.45, 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.[39]

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 196 out of 676 unique firms which at any time participated in horizontal RJVs.[40]

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,

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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.

[39] We also constructed an alternative measure of research networks, based on both direct and indirect links among competitors; thus accounting for the possibility that firms can also potentially collaborate toward collusion via indirect contacts. The results obtained with this measure are very much in line with our main findings: the critical network size above which market shares of participating firms are significantly negative can be found at $K^{**}=0.16$.

[40] 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).

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 6 shows these and more industries that are suspect under our framework.

[Insert Table 6 about here]

Before going to the extensions and robustness checks, it is worthwhile stating that –while applying rather different identification strategies– our results are very much in line with Goeree and Helland's (2010) and Oxley et al.'s (2009) findings that RJVs in the U.S. may soften product market competition. This correspondence, we believe, strengthens the main message. Yet, the applied methodology allows our study to focus on some unexplored issues – prominently the heterogeneous effect of different forms of RJV participation– and to add to a small but growing body of literature that identifies potential problems of the NCRA industrial policy program.

6. Extensions and robustness checks

Another view on what constitutes a firm

By using the COMPUSTAT Industrials database for the construction of our market share measures, we implicitly assume that firms mainly dedicate resources, take strategic (collusion) decisions, and identify rivals in their most important industry. Indeed, the COMPUSTAT Industrials database assigns all sales of a firm to its primary SIC4 code, which represents its most important industry.

One could assume, on the other hand, that firms distribute resources, take strategic decisions and identify rivals over basically all industries where they are present. We have therefore re-done our analysis with the COMPUSTAT Segment database, which allocates sales (and other relevant figures) over all of a firm's business segments. The correlation between the market shares in the two datasets is equal to 0.37. While this correlation is positive and highly significant (p-value < 0.01), its relatively low value does indicate that we are getting at different aspects of how firms can be allocated into markets.[41] Thus, given that these two databases – COMPUSTAT Industrials versus COMPUSTAT Segment– offer two extreme views of how firms potentially operate, we provide an analysis for both a broad and a narrow approach of how to identify a firm's business and its direct competitors.[42]

Before presenting these new results, however, we need to briefly clarify how we have built the variables with the segment data; see Table 7 for the exact definitions. Of course, the market shares are based on the reported sales per segment. The other firm-specific and industry-level variables use segment-specific observations if available; e.g., the segment database normally reports assets per segment. If not available (e.g., for patents), then we assign the company-wide figure to the segments proportional to their sales.[43]

[Insert Table 7 about here]

As can be seen from Table 8a, a firm's assets, R&D expenditures, etc., are smaller when distributed over all its segments instead of when they are all attributed to its primary SIC4 code. Firms' market shares in the segment database, on the other hand, are on average a bit larger than in the industrials database. Hence, the two databases are comparable, but they indeed offer different views of what constitutes a firm.

[Insert Table 8a about here]

[Insert Table 8b about here]

[41] Oxley et al. (2009) conduct a somewhat similar exercise in identifying a firm's rivals (i) based on only its primary SIC4 code, and (ii) based on all its reported SIC4 codes and state as motivation: "We used both a broad and a narrow approach to identify a firm's business and its rivals" (Oxley et al., 2009 p 1327).

[42] We thank an anonymous referee for leading us to re-do the analysis with the COMPUSTAT Segment data.

[43] One can argue that, even though considering sales in one particular business segment, a firm's consolidated figures –e.g., in R&D– contribute to its market shares in that segment. However, we think it more reasonable that resources are specifically allocated to a particular segment and contribute to its market share there. Moreover, this way of modeling provides the starkest contrast with our methodology applied to the COMPUSTAT Industrials database.

The definitions of horizontal and vertical RJVs need special consideration. First, we consider firm *i* in segment *s* to be participating in a horizontal RJV if it shares the same SIC4 segment *s* with at least one other RJV member. Its network size classes are defined in a similar fashion as for our main analysis. For vertical RJVs, we use two definitions. The first ("RJV Vertical Narrow") identifies firms that participate in an RJV, and the intersection of all of its reported SIC4s with any other RJV-member's set of reported SIC4s is empty. In other words, a firm is considered to be participating in a narrow vertical RJV if it never meets any of its direct competitors in an RJV, counted over all SIC4s in which it participates. This is our main category to identify participation in a vertical RJV, as this is surely the "cleanest" and narrowest way to define vertical RJVs and to identify potentially beneficial innovation effects.

However, it may be that this is actually too narrow a definition if firms' business segments operate totally independently. If this is the case, even if two 'parent firms' meet in another SIC4, two particular business units of these same parent firms may be considered to be participating in a vertical RJV, since there is no connection between these two business units in the relevant product markets. We therefore also construct a second and broader category of vertical RJVs ("RJV Vertical Broad"). In particular, a firm *i* that is present in segment *s* is considered to be participating in a broad vertical RJV if firm *i* participates in an RJV and (i) meets therein no other firms of that same segment *s* in which it is present, but (ii) does meet firms with which it shares *other* segments. Thus, this category identifies RJV participants that are present in a particular business segment and do not compete with other members in this same segment, but do have other segments in common. See Tables 8a and 8b for summary statistics on all our RJV measures.

When looking at the effects of RJV participation based on the segment data (Table 9), one can see that results are qualitatively the same as for our main analysis. In particular, RJV participation of any type does not lead to changes in market shares (see column 1). Its absolute value is close to zero and the effect is not significant. Second, when separating participation into vertical and horizontal RJVs, the impact is now positive for our two categories of vertical RJVs and negative for horizontal RJVs (although not significant). Third, when considering the size of the created horizontal network, participation in small networks has no effect, whereas participation in medium-size and large networks has a significantly negative impact on market shares (see column 3). In this last specification, also participation in narrow vertical RJVs leads to a positive and significant effect, while participation in broad vertical RJVs is not significant. This confirms expectations that narrow vertical RJVs are better able to isolate innovative RJVs. We therefore concentrate further only on narrow vertical networks to investigate the relation between their size and firms' market share.

[Insert Table 9 about here]

As can be seen from Table 10, participation in more (narrow) vertical RJVs – thus thereby creating a large (narrow) vertical "network" – leads to a larger gain in market shares (although the effect is not significant for medium-size networks due to the relatively large standard errors). Thus, narrow vertical RJVs lead to innovative gains that are larger for large created networks.

[Insert Table 10 about here]

The consistent results for both the COMPUSTAT Industrials and Segment databases strengthen the message of the paper. Indeed, both when assigning firms to their primary industry and when allocating firms into all their business segments, we find that if RJV participation with direct competitors leads to large enough networks then firms lose market share as a consequence. Our findings, therefore, are in line with these firms using RJV participation as a tool for product market collusion, for both a grouped and a divisional approach of firms' operations.

Potential measurement error and correlation with other databases

The COMPUSTAT datasets may lead us to measure market shares with some error since product markets for antitrust matters are generally more narrowly defined than industries or segments.[44] While measurement error in our dependent market-share variable does not create biased estimates, the fact that we include a lagged market-share as an independent variable may lead to "regression dilution" or "attenuation

[44] Moreover, firms may strategically misrepresent some segments in the COMPUSTAT Segment database; although this misrepresentation should to a large extent be remedied by new accounting standards in the U.S., as is extensively argued by Berger and Hann (2003). See also Bloom et al. (2012) who discuss the pros and cons of the COMPUSTAT Segment dataset and show that there is a high correlation between this database and another prominent commercial dataset on segment data (Amadeus).

bias”. Indeed, the greater the variance of the potentially wrongly measured lagged market-share, the closer its estimated coefficient approaches zero, instead of measuring the true relation.

However, the system GMM estimator that we employ deals well with measurement error. First, any permanent additive measurement errors are of course absorbed into the time-invariant individual effects, and are hence controlled for. But second, the system GMM estimator allows for transient measurement errors. As Bond et al. (2001) neatly show, twice-lagged first-differences of the market share series can still be used as instrumental variables for the levels equations in the presence of serially uncorrelated measurement error. Therefore, if the lagged dependent variable is measured with error, this will require period $t-1$ first-differences of the variables measured with error to be omitted from the set of instruments for the equations in levels.

We thus need (i) no serial correlation in any potential measurement error and (ii) to use further than $t-1$ differenced lags as instruments in the levels equation. First, the Arellano-Bond tests show that we do not have serial autocorrelation in the error term in any of our specifications. Thus, this indicates that any potential measurement error in our data is also serially uncorrelated. Furthermore, we use lags t-2 or further in our GMM analysis; see footnote 35 for more details on our instruments. We, therefore, fully employ the advantages of the system GMM estimator to deal with potential measurement error. Indeed, Bond et al. (2001, pp 14) state that: “The potential for obtaining consistent parameter estimates even in the presence of measurement error and endogenous right-hand side variables is a considerable strength of the GMM approach [in dynamic panel data models].”

Nevertheless, to further show that our market share measures are suited for our purposes, we compare our market shares with those of other databases that could provide us with potentially “better” market shares measures, since they are based on well-defined relevant antitrust markets. We then investigate how these market share measures correlate with ours over the years in the sample. The existence of a positive correlation would imply that the changes in one series of market shares are reflected as well in the market share changes of the other series. Since we are exactly relying on this time series variation for identification in our panel data methodology, i.e., changes in market shares due to RJV participation, a positive correlation would then show that databases are comparable in terms of firms' shifting relative positions in their markets.

For this purpose, we employ the datasets of the studies that are most related to ours in methodology or topic. First, given that Gugler and Siebert's (2007) study is the most similar in terms of methodology (they also identify market power through market share changes), we also use firms' annual market shares of the U.S. semiconductor industry (SIC4 industry 3674 "Semiconductors and Related Devices") from the Gartner Group. This company annually collects production data for each firm operating in the semiconductor industry. Thus, this data covers the whole population of firms actively competing in one well-defined (antitrust) product market.

Second, Goeree and Helland (2010) is the paper closest to ours in topic. Their study applies not only the COMPUSTAT Industrials database, but also the Gartner database and data from the Federal Communication Commission (FCC) on telecom companies (SIC4 industry 4813 "Telephone Communications"). This FCC dataset contains the whole population of firms actively competing in one relatively well-defined product market. We therefore also consider the FCC dataset.

As can be seen from Table 11, the correlations between our market share measures and those of the FCC and Gartner datasets are high. First, over all years in our sample, the correlation between the FCC market shares and our COMPUSTAT Industrials and Segment market shares are 0.95 and 0.97, respectively. On a year-by-year basis, correlations between the FCC and COMPUSTAT market shares are often higher than 0.99 and never lower than 0.81. Apart from a few exceptions, the p-values for these yearly correlations are lower than 0.01. The same pattern can be observed when we compare our data with the Gartner data. Over all years of our sample, the correlation between the Gartner market shares and our COMPUSTAT Industrials and Segment market shares are 0.90 and 0.91, respectively. On a year-by-year basis, the correlations between the Gartner and COMPUSTAT market shares are at minimum 0.90, but again for several years higher than 0.99. All these correlations are significant at the 1% level.

[Insert Table 11 about here]

In sum, we observe almost perfect positive correlations between our market shares and the FCC and Gartner datasets. The existence of this correlation between "true" market share measures and those provided by the two COMPUSTAT databases can be taken as additional evidence that our market shares capture the relevant dynamics.

Market share-weighted networks

It seems perhaps intuitive that collusion would be more problematic if the largest firms in an industry are linked rather than the smallest. In other words, market shares of the linked firms may matter as well. We therefore further build a second network measure ('RN_MS') which takes into account the relative size of member firms. In particular, we create the same RJV network-participation measure as in equation (2), but weigh contacts now by firms' market shares; see Tables 1 and 11 for the exact definition in the COMPUSTAT Industrials and Segment databases, respectively.

The distribution of this market share-weighted network lies more to the right than the distribution of our original variable; i.e., when taking into account market shares, firms' horizontal networks cover relatively more of their industries. Indeed, the relative average horizontal network ('Horizontal Network MS') is 0.2812, which is almost double our average original network variable (0.1478). This difference is confirmed when creating three different size classes for the market share-weighted measure in the same fashion as before, and comparing these with our original network. In particular, when weighting networks with market shares, the COMPUSTAT Industrials database shows that small networks cover about 3% of their industry, whereas medium-size networks cover 25% and large networks 59%. These numbers are clearly higher than the size classes of our original network measure (about 2%, 9% and 39%, respectively; see Table 2b). The (unreported) differences for the segment data are even higher.

Our two network variables thus measure different but complementary concepts. Indeed, our first measure builds solely upon the number of competitors that is connected through RJV participation, while the second puts more emphasis on their relative size.[45] This difference makes it interesting to see if our results change by taking this dimension into account.

[45] Accordingly, we can tentatively interpret small market share-weighted networks as being networks with prevalently relatively small firms, while large networks mainly contain large firms.

For both our datasets, the market share-weighted networks yield qualitatively the same findings as our main specification (see Table 12). In other words, whereas participation in small networks yield positive but insignificant changes in market shares, participation in medium-size and large networks yield negative and significant changes in market shares. Moreover, participation in vertical networks again results in a positive effect on market shares. Thus, our message that large networks tend to facilitate collusion holds, independent of whether we define networks in terms of number of firms or in terms of their market share. Furthermore, these results largely confirm that networks of larger firms have a more negative impact on participating firms' market shares than networks of small firms.

[Insert Table 12 about here]

Given that our findings indicate that the relative size of a firm matters for collusion, it is interesting to further empirically separate its collusive effects. In particular, we can re-do our analysis focusing on firms' size as a main explanatory variable instead of the size of their horizontal network. For that purpose, we partition participants of horizontal RJVs into three groups: small firms (with market shares in the first quartile of the distribution), medium-size firms (second and third quartiles), and large firms (last quartile). For both COMPUSTAT databases, our (unreported) results show the effect of horizontal RJV participation to be indeed stronger for relatively larger firms.

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 sufficient 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 196 out of 676 unique firms which at any time participated in horizontal RJVs.

Our findings are robust to different specifications of a firm's business and its direct competitors. In particular, for both a grouped and a divisional approach of a firm, results indicate that participation in large horizontal networks is most conducive to collusion in the product market. We furthermore tentatively show that especially larger firms cause more collusive harm through their RJV participation.

In terms of policy, our findings are rather worrisome as they suggest that a large number of firms create networks that enable collusion in the product market and lead 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, and on the size of its participating firms. 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 identified 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 U.S. 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.

Unfortunately, our methodology cannot distinguish between tacit and explicit collusion. Whenever firms collude and coordinate on higher prices (or lower quantities) through RJV participation, they decrease their market share with respect to rivals. *How* exactly they coordinate –i.e., tacitly or explicitly– is hard to determine. This is not an artifact of our methodology, but a common issue in virtually all empirical and theoretical papers on collusion to date, in the sense that no distinction is being made between the two modes of collusion; see Cooper and Kühn (2011) for a discussion on the issue of explicit communication in collusion and their call for more research on this important dimension of collusion.

This matters for policy purposes since only explicit collusion is illegal. Of course, one might argue that collusion is already explicit when firms meet only once. They can use then this one-off meeting to agree on the exact behavioral rules that are identical to what would have emerged under coordination toward tacit collusion (Harrington, 2006). In other words, collusion can be considered explicit when firms meet once (or more) to agree on a collusive equilibrium. In that sense, one can tentatively hypothesize that firms that meet regularly in RJVs to coordinate on prices and quantities use these meetings to collude explicitly. However, more detailed information on cartels' internal organization is needed.

Indeed, as a final remark, while our findings indicate that RJVs are used to facilitate collusion in the product market, it is essential to understand how these cartels would be organized in practice. Unfortunately, this is a somewhat difficult point due to a lack of information on the internal workings of U.S. cartels, both in general and related to RJVs. The Department of Justice and the Federal Trade

Commission regularly issue press releases on detected cartel cases, but these are usually one or two pages in length and provide little details as to how cartels actually function.

Harrington (2006) investigates primary source material for decisions made by the European Commission (E.C.).[46] While his study indicates that it is striking how sophisticated their organizational structure generally is, the allocation of duties across firms' employees in the discovered cartels is normally such that the top-level people of the participating firms are involved. One particular NCRA-RJV that has been suspect of collusive conduct, indeed, had the top-level management of its member-firms active in the board.[47] From this, one can tentatively conclude that collusion in NCRA-RJVs would be orchestrated from the highest level. However, in order to improve our understanding of the internal workings of cartels, and consequently to increase their detection, we would encourage antitrust authorities to share more detailed data with academic researchers.

[46] These cases comprise cartel activity that largely covers the 1980s and 1990s in the E.U. The E.C.'s decisions can range from 30 to over 200 pages and provide a lot of information on the manner in which firms colluded.

[47] Addamax Corp. v. Open Software Foundation, 964 F. Supp. 549 (D.Mass. 1997), 152 F.3d 48 (1st Cir. 1998). See also Goeree and Helland (2010) for more details on this case.

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Appendix: Proof of Lemma 1

N firms compete à la Cournot in homogeneous goods. Demand is given by $p(X)$, where *p* is price, *X* is total output, and $p'(X) < 0$. A firm *i*'s cost function is $c(x_i)$, where x_i is firm *i*'s output, and $c_x(x_i)$ its marginal cost. The Cournot equilibrium is a vector $(x_1, ..., x_N)$ such that the first-order condition holds for all *N* firms. We need two weak assumptions on the Cournot equilibrium to hold; these two conditions are among the weaker conditions for Cournot equilibrium (Dixit, 1986). The first condition imposes downward sloping reaction curves,

$$p'(X) + x_i p''(X) < 0. \qquad (1)$$

The second condition states that each firm's residual demand curve intersects its marginal cost curve from above,

$$c_{xx}(x_i) > p'(X). \qquad (2)$$

Write $y_i \equiv \sum_{j \neq i} x_j = X - x_i$ for the aggregate output of all firms other than firm *i*. From the first-order condition, we can derive firm *i*' reaction curve with respect to a change in rivals' aggregate output

$$\frac{dx_i}{dy_i} \equiv R_i = -\frac{p' + x_i p''}{2p' + x_i p'' - c_{xx}^i}. \qquad (3)$$

From condition (1) and firm's *i* second-order condition, $R_i < 0$. Together with condition (2), we then have that

$$-1 < R_i < 0.$$

This means that if firm *i*'s rivals jointly increase production, then firm *i* contracts its production, but by less than its rivals' expansion. From equation (3), we have that $dx_i = R_i dy_i$, which can be rewritten as $dx_i(1 + R_i) = R_i(dx_i + dy_i)$, or

$$dx_i = -\lambda_i dX, \qquad (4)$$

where $\lambda_i \equiv \frac{-R_i}{1+R_i}$. Under conditions (1) and (2), clearly

$$\lambda_i > 0. \qquad (5)$$

Suppose now that we have $k = 1, \dots, K$ firms ("insiders") that produce a total output $\sum_k x_k = X_K$. Write $z_K \equiv \sum_{j \neq k} x_j = X - X_K$ for aggregate output produced by firms other than the *K* insiders. Then, for any rival firm $j \neq k$, and given equation (4), we can write $dx_j = -\lambda_j dX$. Adding up for all firms $j \neq k, dz_K = -\sum_{j \neq k} \lambda_j \, dX$. Adding

dX_K to this equation gives us $dz_K + dX_K = -\sum_{j \neq k} \lambda_j \, dX + \ dX_K$, or rewriting, $dX\left(1 + \sum_{j \neq k} \lambda_j\right) = dX_K$. This leads us to

$$\frac{dX}{dX_K} = \frac{1}{\left(1 + \sum_{j \neq k} \lambda_j\right)}$$

From result (5), we know that $\lambda_j > 0$. Thus,

$$0 < \frac{dX}{dX_K} < 1. \qquad (6)$$

Therefore, if a group of K firms (exogenously) change their output by an amount of dX_K, the change in total output dX moves in the same direction, but by less. QED.

Tables and Figures

Table 1: Variable Definitions

Variable	Definition
Market share (MS_{imt})	Firm *i*'s market share in its primary SIC4 industry *m* 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 U.S. $.
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 a 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 the competitor is defined as a firm with the same primary SIC4 .
Total $Assets_{it}$	Firm *i*'s total assets in year *t*, in million U.S. $.
$R\&D_{it}$	Firm *i*'s R&D expenses at year *t*, in million U.S. $.
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).
Horizontal Network (RN_{imt})	Number of links with SIC4 competitors through RJV participation (defined as firms with the same primary SIC4), over the total number of possible links in the same SIC4.
Horizontal Network MS (RN_MS_{imt})	Sum of the market shares of all competitors (defined as firms with the same primary SIC4) linked through RJV participation.
$R\&D\_Industry_{mt}$	Industry average yearly R&D expenditures at the SIC4 level, in million U.S. $.
$MarketValue\_Industry_{mt}$	Industry average yearly market value at the SIC4 level, in million U.S. $.

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
Obs.	59,996		5,987		2,366		3,621	

Table 2b: Preliminary Statistics for Horizontal Networks in Different Size Classes

	Small		Medium-size		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
Obs.	905		1,811		905	

Table 3: Determinants of 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: 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}	0.9006***	0. 9230***	0.9159***
	(0.0146)	(0.0176)	(0.0437)
Cumul. RJV effect - Any	-0.0024		
	(0.0050)		
Cumul. RJV effect - Vertical		0.0481**	0.0446**
		(0.0205)	(0.0205)
Cumul. RJV effect - Horizontal		-0.0091	
		(0.0073)	
Cumul. Netw. effect – Horiz. -Small			-0.0095
			(0.0129)
Cumul. Netw. effect - Horiz. -Medium			-0.0137*
			(0.0071)
Cumul. Netw. effect - Horiz. -Large			-0.0265**
			(0.0138)
Cumul. Log(R&D) effect	0.0005	-0.0012	0.0003
	(0.0013)	(0.0014)	(0.0014)
Log(Market Value)_Industry$_{t-1}$	-0.0002	-0.0004	-0.0001
	(0.0004)	(0.0005)	(0.0005)
Log(R&D)_Industry$_{t-1}$	0.0032	0.0063*	0.0024
	(0.0023)	(0.0037)	(0.0024)
Constant	-0.0003	-0.0015	-0.0005
	(0.0022)	(0.0028)	(0.0024)
Sargan test (Prob > chi2)	0.3693	0.8063	0.9518
	(113)	(120)	(135)
Difference Sargan test (Prob > chi2)	0.4868	0.4015	0.2886
	(12)	(12)	(12)
Arellano-Bond test (Prob > z)	0.2273	0.6859	0.5937
Number of observations	36,485	36,485	36,485
Number of groups	5,785	5,785	5,785
Number of time periods (max)	12	12	12
Number of instruments	133	123	164

We report System GMM estimates of equation (4). 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-values of the Sargan test and the difference-in-Sargan test (the degrees of freedom are in parentheses) when we exclude the instruments for the level equation, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Table 5: Vertical networks on market shares

Dep. Var.	MS
Estimation Method	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)
Sargan test (Prob > chi2)	0.8084
	(159)
Difference Sargan test (Prob > chi2)	0.7373
	(20)
Arellano-Bond test (Prob > z)	0.8289
Number of observations	36,563
Number of groups	5,785
Number of time periods (max)	12
Number of instruments	188

We report System GMM estimates of equation (4) 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-values of the Sargan test and the difference-in-Sargan test (the degrees of freedom are in parentheses) when we exclude the instruments for the level equation, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Table 6: 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.

Table 7: Variable Definitions - Based on Business Segments

Variable	Definition
Market Share (MS_{ist})	Firm i's market share in its SIC4-segment *s* in a given year *t*. The market share for firm *i* in its segment *s* at time *t* is $MS_{ist} = (total\ sales_{ist} - foreign\ sales_{ist}) / \sum_{i=1}^{N_{st}} (total\ sales_{ist} - foreign\ sales_{ist})$, where N_s is the number of firms in segment *s*. All sales are in million U.S. $.
RJV Any_{ist}	Dummy equal to 1 if firm *i* in segment *s* participates in at least one RJV at year *t*.
RJV $Vertical\_narrow_{ist}$	Dummy equal to 1 if firm *i* in segment *s* participates in an RJV and the intersection of all of its reported SIC4-segments with any other RJV-member's set of reported SIC4-segments is empty.
RJV $Vertical\_broad_{ist}$	Dummy equal to 1 if firm *i* in segment *s* participates in an RJV and (i) meets therein no other firms of that same segment *s*, but (ii) meet firms therein with which it shares other segments.
RJV $Horizontal_{ist}$	Dummy equal to 1 if firm *i* in segment *s* participates in at least one RJV and its shares therein the same SIC4 segment *s* with at least one other RJV member.
Total $Assets_{ist}$	Firm *i*'s total assets in segment *s* in year *t*, in million U.S. $. If missing, the value is computed proportionally to firm's *i* sales in segment *s* relative to firm's *i* total sales.
$R\&D_{ist}$	Firm *i*'s R&D expenses in segment *s* at year *t*, in million U.S. $. If missing, the value is computed proportionally to firm's *i* sales in segment *s* relative to firm's *i* total sales.
Patent $stock_{ist}$	Firm *i*'s share of cumulated patents in segment *s* 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). The share is computed proportionally to firm's *i* sales in segment *s* relative to firm's *i* total sales.
Horizontal Network (RN_{ist})	Number of links with SIC4-segment competitors through RJV participation, divided by the total number of possible links in the same segment *s*.
Horizontal Network MS (RN_MS_{ist})	Sum of the market shares of all SIC4-segment competitors linked through RJV participation.
$R\&D\_Industry_{st}$	Industry average of yearly R&D expenditures at the SIC4-segment level, in million U.S. $.
Total $Asset\_Industry_{st}$	Average yearly Total Assets at the SIC4-segment level, in million U.S. $.

Table 8a: Preliminary Statistics for Different Categories of RJV Participants versus Non-participants - Based on Business Segments

	No RJV		Any RJV		Vertical narrow RJV		Vertical broad RJV		Horizontal RJV	
Variable	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Market Share	0.1194	0.2328	0.1447	0.2216	0.1848	0.2414	0.2206	0.2813	0.0776	0.1255
Total Assets	546.8278	4,765.3570	4,083.5630	14,947.8100	2,948.6910	9,147.7770	2,480.0880	12,514.1700	5,566.1610	17,572.9400
R&D Expenditures	2.0729	147.1867	85.4811	368.3811	27.9078	90.5893	24.3691	78.6285	142.4221	494.5315
Patent stock	3.0590	73.9138	87.3088	298.8605	55.2422	188.1465	43.3479	116.3488	127.6442	393.4492
# Horiz. RJVs	-	-	1.9425	4.9605	-	-	-	-	3.6567	6.3289
Horizontal Network	-	-	-	-	-	-	-	-	0.1067	0.1290
Obs.	80,520		10,779		2,230		2,823		5,726	

Table 8b: Preliminary Statistics for Horizontal Networks in Different Size Classes - Based on Business Segments

	Small		Medium-size		Large	
Variable	mean	sd	mean	sd	mean	sd
Market Share	0.0273	0.0604	0.0713	0.1120	0.1404	0.1664
Total Assets	4,482.7560	17,500.7000	5,936.4170	18,686.4100	5,907.5820	15,152.4700
R&D Expenditures	53.7644	190.0433	112.4512	320.4915	290.6491	839.2496
Patent stock	45.3684	153.9146	119.1152	365.7461	226.1154	556.9792
# Horiz. RJVs	1.6504	2.1483	3.3952	5.1820	6.1792	9.5544
Horizontal Network	0.0148	0.0068	0.0704	0.0299	0.2709	0.1632
Obs.	1,430		2,862		1,434	

Table 9: RJV Participation on Market Shares -
Based on Business Segments

	RJV any	Horiz. vs. Vertical	Horizontal Network
Dependent Variable	MS	MS	MS
Estimation Method	System GMM	System GMM	System GMM
MS $_{t-1}$	0.8560***	0.8442***	0.8044***
	(0.0630)	(0.0615)	(0.0643)
Cumul. RJV effect - Any	0.0001		
	(0.0067)		
Cumul. RJV effect - Vertical (narrow)		0.0433	0.0393*
		(0.0301)	(0.0227)
Cumul. RJV effect - Vertical (broad)		0.0164	0.0016
		(0.0130)	(0.0090)
Cumul. Netw. effect – Horiz.		-0.0057	
		(0.0076)	
Cumul. Netw. effect – Horiz. -Small			-0.0081
			(0.0058)
Cumul. Netw. effect - Horiz. -Medium			-0.0126**
			(0.0059)
Cumul. Netw. effect - Horiz. -Large			-0.0186**
			(0.0097)
Cumul. Log(R&D) effect	0.0031**	0.0026**	0.0026***
	(0.0012)	(0.0012)	(0.0009)
Log(Total Assets)_Industry$_{t-1}$	0.0074***	0.0072***	0.0033***
	(0.0013)	(0.0012)	(0.0005)
Log(R&D)_Industry$_{t-1}$	-0.0027	-0.0007	0.0024
	(0.0029)	(0.0028)	(0.0018)
Constant	-0.0297***	-0.0307***	-0.0109***
	(0.0066)	(0.0066)	(0.0027)
Sargan test (Prob > chi2)	0.4386	0.5364	0.1589
	(114)	(168)	(331)
Difference Sargan test (Prob > chi2)	0.3415	0.3065	0.7227
	(60)	(60)	(60)
Arellano-Bond test (Prob > z)	0.5593	0.6859	0.5565
Number of observations	55,304	55,304	55,304
Number of groups	10,490	10,490	10,490
Number of time periods (max)	12	12	12
Number of instruments	134	194	363

We report System GMM estimates of equation (4). 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-values of the Sargan test and the difference-in-Sargan test (the degrees of freedom are in parentheses) when we exclude the instruments for the level equation, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

**Table 10: Vertical Networks on Market Shares -
Based on Business Segments**

Dep. Var.	MS
Estimation Method	System GMM
MS $_{t-1}$	0.7945***
	(0.0691)
Cumul. RJV effect – Horizontal	-0.0155**
	(0.0072)
Cumul. Netw. effect – Vertical (narrow) - small	0.0507*
	(0.0295)
Cumul. Netw. effect - Vertical (narrow) - medium	0.0435
	(0.0361)
Cumul. Netw. effect - Vertical (narrow) - large	0.0760**
	(0.0349)
Cumul. Netw. effect - Vertical (broad)	0.0032
	(0.0117)
Cumul. log(R&D) effect	-0.0032**
	(0.0014)
Log(Total Asset)_Industry$_{t-1}$	-0.0039***
	(0.0009)
Log(R&D)_Industry$_{t-1}$	-0.0025
	(0.0037)
Constant	-0.0131***
	(0.0037)
Sargan test (Prob > chi2)	0.1953 (255)
Difference Sargan test (Prob > chi2)	0.8434 (60)
Arellano-Bond test (Prob > z)	0.5547
Number of observations	55,304
Number of groups	10,490
Number of time periods (max)	12
Number of instruments	287

We report System GMM estimates of equation (4) 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-values of the Sargan test and the difference-in-Sargan test (the degrees of freedom are in parentheses) when we exclude the instruments for the level equation, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Table 11: Correlation Coefficients among Different Measures of Market Shares

	COMPUSTAT Industrials		COMPUSTAT Segment	
Year	MS FCC	MS Gartner	MS FCC	MS Gartner
1986	0.9594 **	-	0.9786 **	-
1987	0.9995 ***	-	0.9995 **	-
1988	0.9993 ***	-	0.9994 **	-
1989	0.9984 ***	0.9379 ***	0.9967 ***	0.9959 ***
1990	0.9963 ***	0.9055 ***	0.9917 ***	0.9968 ***
1991	0.9957 ***	0.9200 ***	0.9924 ***	0.9979 ***
1992	0.9934 ***	0.9228 ***	0.9873 **	0.9960 ***
1993	0.9914 ***	0.9496 ***	0.9873 ***	0.9973 ***
1994	0.9903 ***	0.9709 ***	0.9851 ***	0.9464 ***
1995	0.9813 ***	0.9868 ***	0.9759 ***	0.9655 ***
1996	0.9968 ***	0.9937 ***	0.9872 ***	0.9546 ***
1997	0.8558 ***	0.9965 ***	0.8438 ***	0.9720 ***
1998	0.8188 ***	0.9969 ***	0.8322 ***	0.9681 ***
1999	0.8961 ***	0.9920 ***	0.9527 ***	0.9601 ***
Tot.	0.9546 ***	0.8957 ***	0.9669 ***	0.9143 ***

We report the pair-wise correlation coefficients between the market shares based on data from COMPUSTAT Industrials (in the first two columns) and COMPUSTAT Segment (third and fourth column) and the market shares from the FCC database and Gartner database respectively. The symbols *** and ** represent significance at the 1% and 5% level, respectively.

Table 12: RJV Participation on Market Shares - Based on Market Share-Weighted Network Measure

	Horizontal Network (MS-based)	Horizontal Network (MSseg based)
Dependent Variable	MS	MS
Estimation Method	System GMM	System GMM
MS_{t-1}	0.9100***	0.7965***
	(0.0466)	(0.0599)
Cumul. RJV effect – Vertical	0.0489**	
	(0.0192)	
Cumul. RJV effect - Vertical (narrow)		0.0364*
		(0.0229)
Cumul. RJV effect - Vertical (broad)		0.0038
		(0.0087)
Cumul. Netw. effect – Horiz. –Small	0.0037	0.0068
	(0.0096)	(0.0058)
Cumul. Netw. effect - Horiz. –Medium	-0.0167*	-0.0101*
	(0.0087)	(0.0059)
Cumul. Netw. effect - Horiz. –Large	-0.0166**	-0.0127*
	(0.0068)	(0.0075)
Cumul. Log(R&D) effect	0.0001	0.0024***
	(0.0012)	(0.0008)
Log(Market Value)_Industry$_{t-1}$	-0.0005	
	(0.0005)	
Log(Total Asset)_Industry$_{t-1}$		0.0032***
		(0.0006)
Log(R&D)_Industry$_{t-1}$	0.0038	0.0021
	(0.0023)	(0.0020)
Constant	0.0011	-0.0108***
	(0.0023)	(0.0029)
Sargan test (Prob > chi2)	0.7753	0.2138
	(135)	(331)
Difference Sargan test (Prob > chi2)	0.3891	0.9081
	(12)	(60)
Arellano-Bond test (Prob > z)	0.7522	0.5552
Number of observations	36,485	55,304
Number of groups	5,785	10,490
Number of time periods (max)	12	12
Number of instruments	164	363

We report System GMM estimates of equation (4).Variables in the first column are based on COMPUSTAT Industrials (see table 1), while variables in the second column are based on COMPUSTAT Segment (see table 7). 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-values of the Sargan test and the difference-in-Sargan test (the degrees of freedom are in parentheses) when we exclude the instruments for the level equation, and the p-value for the Arellano-Bond test for zero autocorrelation in first-differenced errors.

Figure 1: Size distribution of horizontal networks

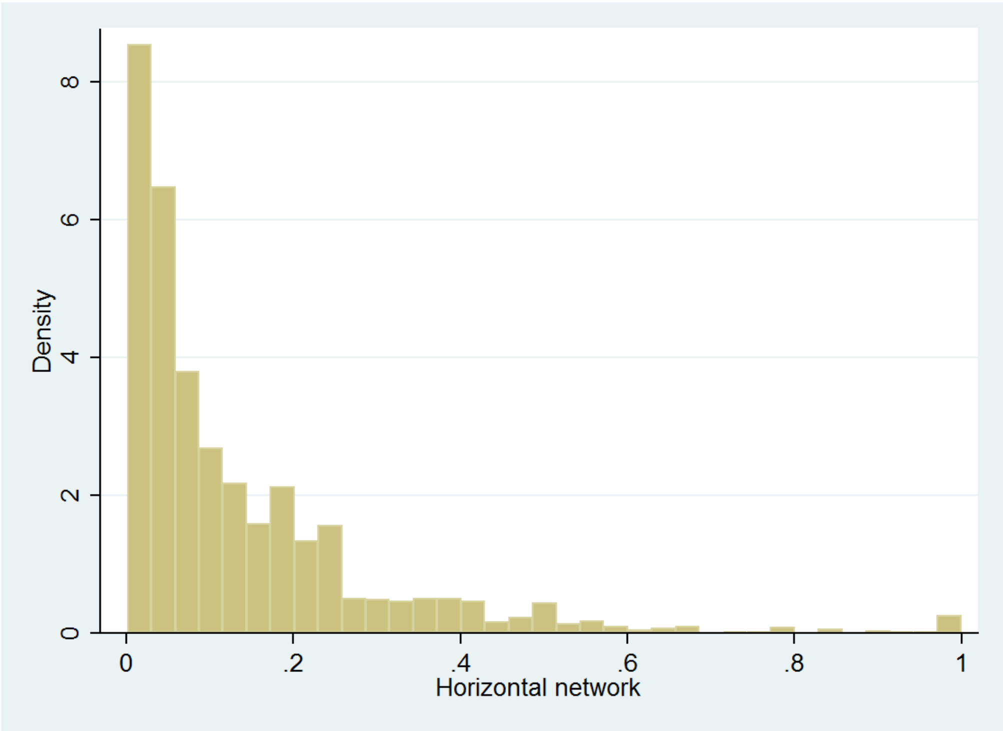

Figure 2: Market Share Impact of Participation in Horizontal Networks: Discrete (three size classes) and Continuous Effects