R&D Spillovers through RJV Cooperation. *

Albert Banal-Estañol,† Tomaso Duso,‡
Jo Seldeslachts§ and Florian Szücs¶

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Abstract

We investigate how R&D spillovers propagate across firms linked through Research Joint Ventures (RJVs). Building on the framework developed by **?** which considers the opposing effects of knowledge spillovers and product market rivalry, we extend the model to account for RJV cooperation. Since the firm's decision to join a RJV is endogenous, we build a model of RJV participation. The outcome equations and RJV participation are then jointly estimated in an endogenous treatment regression model. Our main findings are that the adverse effects of product market rivalry are mitigated if firms cooperate in RJVs; and that RJV participation allows firms to better absorb technological spillovers and, thus, create value.

Keywords: Spillovers, Research Joint Ventures, R&D, Market Value.

JEL Codes: L24, L44, K21, O32

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†Universitat Pompeu Fabra, Barcelona School of Management, Barcelona School of Economics and City University London. E-mail: albert.banalestanol@upf.edu.

‡DIW Berlin, Technical University Berlin, CEPR, & CESifo. E-mail: tduso@diw.de.

§KU Leuven & DIW Berlin. E-mail: jo.seldeslachts@kuleuven.be.

¶Vienna University of Economics and Business. E-mail: fszuecs@wu.ac.at.

1. Introduction

Research and Development (R&D) spillovers have been a major topic of economic research over the last thirty years. The central point of this literature is that the knowledge generated in the R&D process is not entirely private to the innovating firm, but it usually spreads, or "spills over," to other firms through various channels. The types and relative strengths of these channels, the reasons as to why some firms are more subject to spillovers than others, and the ability of firms to appropriate positive spillovers have been analyzed by a large number of studies in the fields of innovation, productivity and industrial organization (see e.g. **?**, for a review).

?, hereafter referred to as BSV, develop a framework that recognizes that R&D generates at least two types of effects on other (receiving) firms: knowledge or technology spillovers, which benefit the firms that are technologically close, and product market effects, which harm firms that are close competitors (also referred to as the business stealing effect). Based on the seminal contribution by **?**, BSV construct two distinct measures of distance between firms to capture these spillovers: first, overlap in the technology classes of firms' patents serve as a measure of technological proximity; second, overlap in the industry segments of their sales indicate product market rivalry. These metrics allow them to distinguish empirically between technology and product market effects. Subsequently, BSV estimate the impact of these two measures on a range of firm performance indicators, such as market value and R&D.[1]

We extend BSV and consider a particular mechanism through which technology spillovers product market effects can be enhanced or mitigated: Research Joint Ventures (RJVs). Firms participating in RJVs may, for instance, benefit more from technology spillovers because of their greater absorptive capacity (**???**), or be more resilient to the effects of

[1] There are a number of recent contributions building on and extending the BSV framework. **?** extend the **?** results to later time periods; **?** identify spillover channels through commonly owned companies; **?** find that synergies obtained from combining innovation capabilities are important consequences of acquisitions.

product market rivalry.[2] Firms may also benefit more from the technological spillovers of their particular RJV partners because they can better internalise these spillovers. Furthermore, as RJVs may be conducive to collusive outcomes (**??**), the negative effect from the R&D of a given competitor may be smaller if this particular competitor is in the same RJV.[3]

Thus, this paper analyzes if and how RJVs affect technology and product market spillovers and, consequently, firm performance. Specifically, we investigate whether RJV membership makes firms different in terms of overall spillover effects, and whether the spillover effects are different between RJV members if compared to non-members (e.g., **?**). More precisely, we first analyse whether RJV-insiders are affected differently by (all) the other firms' research activities (the total spillover pool) than the non-participating firms (RJV-outsiders). Second, we construct a time-varying measure of firm distance in the "RJV dimension," reflecting overlap in the RJVs firms participate in. We then test whether the R&D of companies that meet inside RJVs, i.e., RJV partners, generates different spillover effects than that of non-partners.

Our analysis makes use of the RJVs created under the auspices of the U.S. National Cooperative Research Act of 1984 (NCRA).[4] The NCRA stimulates large-scale inter-firm cooperation agreements in basic research and pre-competitive R&D. These large RJVs, often called "research consortia," were expected to generate and internalize knowledge spillovers. Because of the broad nature of the NCRA program, many firms across several industries entered in RJVs and their participation often changed over time. Therefore, these cooperations provide an excellent empirical setting to investigate the interaction between technological as well as product market spillovers, and RJV participation.

Our empirical strategy takes into account that RJV participation is not a random event, but that firms self-select into cooperation agreements. We explicitly account for

[2] The seminal theory papers on the topic are **?** and **?**, who identify conditions for when RJVs are optimal, depending on the degree of spillovers and the dimensions of collaboration.

[3] In a similar vein, **?** find that Japanese research consortia's patenting is positively associated with their level of technology closeness and negatively with their level of product market overlap.

[4] See **?** and **?** for a discussion of RJVs created under the NCRA.

the self-selection based endogeneity of RJV participation through a selection model of endogenous treatment (see **?**, for a discussion of the appropriate methodological approach). To identify relevant instruments, we build on existing literature on determinants of RJV participation. Specifically, we argue that the firm's positioning in the technological and product market spaces, as well as the firm's absorptive capacity, are potential drivers of RJV participation and employ several proxies for a firm's absorptive capacity. Our probit regression confirms that these variables are economically important and statistically significant drivers of RJV participation, which can thus be integrated in our endogenous treatment framework when assessing the impact of spillovers on outcomes through RJV participation.

Several findings from this integrated framework stand out. First, in the product market space, we show that RJV participation makes firms "more resilient" in the sense of sheltering them from the negative business stealing effects of the R&D of product market competitors. Furthermore, RJV participants competing in similar product markets are able to reduce investment in R&D, leading to a higher firm value as compared to RJV outsiders. Second, in the technology space, RJV participants are better equipped to absorb the R&D of technologically close companies, and thus can reduce their own R&D more in response. We further find some evidence that might indicate that RJV participation leads to too much R&D investment among the technologically close participants. Overall though, RJV participation leads to benefits in the technology space too, as the positive effects of increased absorption on firm value outweigh the negative effects of too much investment in R&D.

The remainder of the paper is structured as follows. Section 2 explains the data and variable construction. Section 3 details determinants of RJV participation, Section 4 discusses the empirical setup and results, while Section 5 concludes.

2. Data and Measurement

2.1. Data Sources

Our data are based on three sources: the NBER U.S. Patent Citations Data File (1970-2001), the Compustat North America Industrials database, containing firm-specific information on publicly traded U.S. firms (1986-2000), and the NCRA-RJV database, which holds information on RJVs and their participants under the NCRA (1985-1999).

A large part of this data – i.e. the Compustat balance sheet data as well as the patent data – overlaps with the dataset provided by BSV, which constitutes the base for our estimation sample.[5] The BSV sample contains 830 firms in the technology space and 828 firms in the product market space. BSV merge these observations with information on R&D expenditures for the 1980-2001 period. Because this dataset is publicly available and has been used in the past, we do not describe it in depth but only provide some key information. For each firm contained in the sample, BSV report information on market value, total assets, employees, sales, and R&D expenses.[6] Based on these variables they then construct Tobin's Q (market value divided by the stock of non-R&D assets) and R&D intensity (R&D expenses divided by sales). They match this data to patent data and report the patent count, as well as a measure of cite-weighted patents. Finally, they also use R&D stock, the number of patents in different technology classes, as well the sales in different four digit industries to construct the measures of product market and technology spillovers that are thoroughly described in section 2.2.[7]

We match this base dataset with information on RJV participation stemming from the

[5]Both the sample and the code are publicly available in the supplementary section of the BSV paper https://www.econometricsociety.org/publications/econometrica/2013/07/01/identifying-technology-spillovers-and-product-market-rivalry.

[6]Firm value is obtained by summing the values of common stock, preferred stock, and total debt net of current assets. The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles other than R&D.

[7]R&D stock is constructed based on the perpetual inventory method. Thus the R&D stock (G) in year t is $G_t = R_t + (1-\delta)G_{t-1}$, where R is the R&D flow expenditure in year t and δ is assumed to be 15%. For the first year of observation they assume that G is in steady state.

NCRA program (for a more detailed description see ??).[8] The NCRA 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 NCRA allows U.S. companies to establish large research cooperations – which we term RJVs – to conduct pre-competitive R&D together. The act has been implemented by the U.S. Congress as part of an industrial policy to improve the international competitiveness of U.S. companies. 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 (?). The reporting requirements make this data well suited for academic research.

In particular, the NCRA database contains information on U.S.-based RJVs during the 1985-1999 period and it provides a great source of information on the composition of large RJVs across U.S. industries, essentially mapping all major basic pre-competitive research agreements undergone in the U.S. during that period. Moreover, given that the nature of the program is to create large pre-competitive research collaborations among companies within the same industry –with the specific aim to improve U.S. innovation– this data is particularly suited to investigate questions regarding research spillovers among companies that are close in the product market and technology spaces.

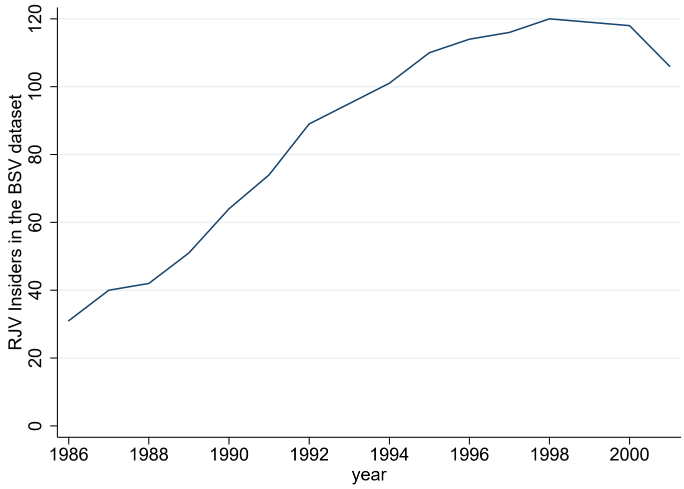
Our original database contains 5,755 NCRA for-profit entities, out of which we match 1,095 to firms in the Compustat North America Industrials database.[9] Out of the 1,095 firms participating in the NCRA-RJVs that we matched to Compustat, 185 are also contained in the BSV data. Thus, about a quarter of the 830 firms contained in the BSV data participate in RJVs during the sample period, where the 185 RJV-insiders participate in a total of 458 RJVs.

Our data also display dynamics over time, as several firms do not continuously par-

[8]We thank Nicolas Vonortas for making the NCRA data available to us.

[9]The non-matched firms are mostly small and, in a few cases, non-U.S. firms. The data also contain non-profit entities such as universities and other government organizations. On average, there are between 1 and 2 non-profit organizations participating in a RJV (?).

Figure 1: Number of RJV Participants over Time



ticipate for the entire sample period. Figure 1 shows the evolution of RJV insiders over time. Each RJV has an average (median) of eight (four) members, but there is much variation. Firms' participation in RJVs changes over time, although we only observe an exit date for 1/6th of RJV affiliations.[10]

The sample of RJV-outsiders in an industry and a given year is generated by taking all those firms which are part of the BSV database but did not participate in any RJV in that industry and given year, where an industry is defined according to the firms' primary SIC4 codes.[11] The number of outsiders changes over time: while some firms are outsiders for the entire sample period, others switch between being insider and outsider. The breadth of the coverage of our database, the goal of the involved RJVs, as well as the time variation, thus, make our data well-suited to investigate how RJV participation impacts spillover effects.

[10] RJV affiliations without an exit date are assumed to last from the date of entry to the end of the sample period. When focusing on RJVs with exit date, participation lasts for an average of 3.1 years.

[11] We exclude the firms that compete in industries with no RJV from our sample of outsiders, since these firms do not face any insiders.

2.2. Measures of Proximity

Since the measures of proximity in the technology and product space are key to construct the main explanatory variables in our regressions, and because we add a measure of RJV proximity to the original variables constructed by BSV, we describe them in depth in this section. First, following BSV we take the measures of technology and product market relatedness to be static, because of the limited variability in the underlying data.[12] RJV links, on the other hand, change every year with firms' dynamic participation in RJVs, which implies we can make relatedness in the RJV space dynamic.

Technology space

We start with the NBER patents database, containing around 2.3m patents in the 1970-1999 period. Of these patents, 443,490, belonging to 407 tech classes, can be matched to the 830 firms contained in the BSV sample. We calculate the share of each firm's patents in each tech class, obtaining a 830 (firms) times 407 (technology classes) matrix, containing all firm-specific vectors $T_i = (T_{i1}, ..., T_{i407})$ with T_{ik} being the share of patents of firm i in the technology class k. From this matrix T, we calculate the correlations between all firms' technology portfolios as:

$$TECH_{ij} = \frac{T_i}{\sqrt{T_i T_i'}} \times \left(\frac{T_j}{\sqrt{T_j T_j'}} \right)'. \tag{1}$$

Thus, we know for each pair of firms (i, j) to which degree their technology portfolios are related. For $i \neq j$, the mean (median) correlation is 0.036 (0.002) and the 95th (99th) percentile is 0.18 (0.48).

[12] We thank a reviewer and the editor to clarify this point. It is surely true that technology and market positions are evolving, but to make progress on this kind of study, one has to assume they can be treated as fixed over some interval. The measure of product market relatedness is static, as it is based on SIC4 codes and entry and exit into a SIC4 code sector is a rare event in our data. The technology measure is based on patents. There is more variation in the patent data, but not enough to meaningfully make it dynamic. Better and more dynamic data would be a step forwards and interesting for future work.

Product market space

We link the average per-segment sales information from the Compustat database across 762 Standard Industry Classification (SIC) codes to 828 firms. Similar to above, we first calculate a 828 (firms) $\times$ 762 (industries) matrix, containing all firm-specific vectors $S_i = (S_{i1}, ..., S_{i762})$ with S_{ik} being the share of sales of firm i in SIC industry k. From this matrix S, we calculate the correlations between all firms' per-segment sales as:

$$SIC_{ij} = \frac{S_i}{\sqrt{S_i S_i'}} \times \left(\frac{S_j}{\sqrt{S_j S_j'}} \right)'. \tag{2}$$

Thus, SIC_{ij} measures the correlation of firms' sales across segments. It is zero up to the 90th percentile, with the 95th (99th) percentile at 0.013 (0.351) and a mean of 0.011.

RJV space

The 185 insiders participate in a total of 458 RJVs. Thus, for each year t, we create a 185 (firms) $\times$ 458 (RJVs) matrix R_t, containing 185 firm-level vectors $R_{it} = (R_{i1t}, ...R_{i458t})$ with R_{ikt} being equal to 1 if firm i participates in RJV k in year t. This matrix contains information on whether two firms i and j were participants in the same joint venture(s) in year t. As above, we calculate, from this matrix R_t, the correlation between firms' vectors of RJV participation:

$$RJV_{ijt} = \frac{R_{it}}{\sqrt{R_{it} R_{it}'}} \times \left(\frac{R_{jt}}{\sqrt{R_{jt} R_{jt}'}} \right)'. \tag{3}$$

Thus, the RJV matrices R_t are calculated for every year t in the sample period and the correlation of firms in the RJV space changes over time. Further, while the previous metrics were calculated for all pairs of firms, RJV-relatedness is calculated only for the subsample of RJV participants. Of course, for all other firms this measure is zero.

2.3. Spillover measures

Based on the proximity measures, we follow BSV and construct measures of technology and product market spillovers. The time-varying (total) spillover pools for product market and technology relatedness are constructed by summing up, for every year and every firm, the R&D expenditures of all other firms in that year, weighted by their (time-invariant) proximity in technology or product market space. Thus, if firms i and j have a non-zero correlation in technology space (i.e., have patented in similar technology classes), then firm j's R&D enters firm i's spillover pool. Therefore, the technology spillover pool is defined as:

$$SPILLTECH_{it}^{tot} = \sum_{j \neq i} TECH_{ij} \times RD_{jt}, \tag{4}$$

where $TECH_{ij}$ denotes the technological correlation of firms i and j and RD_{jt} denotes firm j's R&D spending at time t. The product-market spillover pool is constructed analogously:

$$SPILLSIC_{it}^{tot} = \sum_{j \neq i} SIC_{ij} \times RD_{jt}. \tag{5}$$

In addition, we create another set of partner spillover pools taking the RJV-relatedness of firms into account:

$$SPILLTECH_{it}^{par} = \sum_{j \neq i} RJV_{ijt} \times TECH_{ij} \times RD_{jt}, \tag{6}$$

and

$$SPILLSIC_{it}^{par} = \sum_{j \neq i} RJV_{ijt} \times SIC_{ij} \times RD_{jt}. \tag{7}$$

The partner spillover pools for RJV-insiders count only R&D expenditures by other RJV participants and weigh them with how closely-connected they are in the RJV dimension.

2.4. The Estimation Samples

Since the first step in our analysis consists of replicating the results of BSV, we follow their code and generate our estimation samples by dropping some observations with missing or jumping values on sales and employment and restricting the sample to the 1985-2000 period. Moreover, because we lag all our instruments in our model of RJV participation, we lose the first year of the BSV sample. Finally, we harmonize the sample on which we estimate our two main outcome equations – R&D and Tobin's Q – so that the results are more easily comparable and not driven by sample selection. The final sample is an unbalanced panel containing 9,160 observations. Table 1 reports summary statistics of the main variables used in the regressions.

[Insert table 1 about here]

3. Determinants of RJV Participation

The key insight of our paper is that RJV participation is a central mechanism through which technology and product market spillovers can be mitigated. However, RJV participation is a choice made by the firm. In this section we identify, based on existing literature, important determinants of RJV participation, which can be used as instruments in our framework. We describe different potential drivers in turn: a firm's positioning in the technological and product market spaces; several dimensions of absorptive capacity through a firm's size, R&D intensity, and patent pool; and a firm's (individual) cost of performing R&D. We then show in a probit regression how these drivers impact RJV participation in our sample. This regression is integrated in our more general framework in section 4, where we assess how endogenous RJV participation mediates the effects of technology and product market spillovers on outcomes variables through an endogenous treatment model.

3.1. Technological and product market proximity

Technology space

The literature has argued that, for a company to efficiently assimilate knowledge in an RJV, at least a portion of that knowledge should be similar to its existing know-how. Indeed, technological overlap enhances the ability of RJV participants to understand each other's knowledge and to replicate tacit elements of it (see e.g., **?** and **?** for an overview). Several studies offer rationales and empirical evidence confirming the impact of technological overlap on RJVs. **?** show that technology spillovers positively influence RJV participation. They investigate how RJVs are formed under the umbrella of the Eureka and EU Framework Programmes, two pan-European initiatives aimed at enhancing inter-firm research cooperation, and similar in aim to the NCRA program. Technology spillovers are measured through different proxies, but most relevant for our study, by a measure of the speed at which innovations diffuse throughout sectors (**?**). They find that RJVs are more likely to materialise in sectors where technological knowledge diffuses faster. In related studies, **?** find that sector-level technology spillovers have a positive impact on RJV outcomes in Belgian RJVs –and hence on RJV participation– whereas **?** find a non-linear impact of technological proximity on alliance formation and mobility of active inventors in the US semiconductor industry. In the latter work, technological proximity is measured through patent overlap at the dyadic level. In sum, while a variety of underlying mechanisms, measures, and outcomes have been discussed and observed in the literature, it is clear that technological overlap matters for RJV participation.

Product market space

Prior literature has studied how product market interactions have an impact on RJV participation, with different views and results, as reviewed by **?**. For example, using data from the same NCRA program as our sample, **?** argue that higher industry concentration –i.e., the inverse of competition– increases the benefits of applying generated knowledge, which creates a competitive advantage. In addition, greater concentration makes it easier for firms to identify appropriate research partners within the industry. **?** and **?** also use an industry-level measure of product market competition to explain RJV formation in a European and US context, respectively. All above-mentioned papers find that when product market concentration increases, the likelihood of RJV formation goes up. Instead, **?** hypothesize a positive relationship between competition and RJV participation, suggesting that firms form ties to reduce the uncertainty created by a competitive environment and, by doing so, secure access to innovation resources. They provide empirical correlations to support these claims. Furthermore, RJVs might not only allow for enhanced spillovers and R&D cost-sharing but also for a better R&D coordination (?) and even lead to a reduction of product market competition between participating firms (?). This, in turn, can affect RJV participation incentives (?). In sum, while a variety of theories, measures and outcomes, have been observed in the literature, product market overlap might have an impact on RJV participation.

Our implementation

Based on the above discussion, our empirical strategy allows RJV participation to depend on the positioning of the focal firm in the technology and product market spaces. However, improving upon most of the cited literature, we use a firm-specific rather than an industry-aggregated or dyad-based measure. Furthermore, in the context of this paper, and in line with BSV, we do not just take into account a focal's firm proximity with other firms in the technology and product market spaces, but weigh this proximity by the R&D expenditures of these other firms. Thus, we are in a good position to capture spillovers.

Specifically, to explain the decision to participate in an RJV we employ one-period lagged measures of spillover pools ($SPILLTECH_{it-1}^{tot}$ and $SPILLSIC_{it-1}^{tot}$). The reasoning for using a lag is two-fold. First, the participation decision might take some time to materialise. Second, and perhaps more important from a practical perspective, through lagging our variables we avoid spurious correlation due two-way causality, under the assumption that the lagged variables are predetermined.[13] Note that we do not employ anticipated RJV spillover pools ($SPILLTECH_{it-1}^{par}$ and $SPILLSIC_{it-1}^{par}$), but take instead total spillover pools as participation drivers. Whereas both would make sense, the reason for our choice is methodological. First, from a conceptual point of view, if taking anticipated RJV spillover pools, one would have to assume that a firm already

[13]This follows the logic of internal instruments from the dynamic panel literature. See ? and in particular ? for a specific application of the methodology to RJV participation. Notice also that, since we use first lags of RJV participation in the outcome equations (see equation (9)), we essentially lag our spillovers variables for two periods with respect to the error term in the outcome equation.

knows not only in which RJV it will participate, but also what other members it will encounter there and how much R&D these other members would perform there in the future. In other words, one would have to assume an extremely high degree of foresight from the potentially participating firm. Second, and perhaps more important, a large part of the firms in our database never participate in RJVs. This means that any RJV-specific instrument is a perfect predictor of (non-)participation in a selection model as ours, and hence not usable.

3.2. Absorptive capacity

An extensive literature has stressed that firms need absorptive capacity in order to assimilate and exploit external knowledge, which in turn has an impact on the decision to participate in an RJV (see e.g. **???**). This absorptive capacity might come from different sources and can be measured by different proxies. Based on the literature, we discuss firm size, R&D intensity, and patent pools.

Firm Size

A firm's size is often used as a proxy for absorptive capacity when studying research co-operation. The argument goes that larger firms have a higher absorptive capacity and thus benefit more from RJV participation due to several reasons. First, fixed costs of participation are relatively lower for large firms, and therefore large firms benefit relatively more from spillovers in an RJV (**??**). Further, larger firms may more effectively exert influence over what happens to the research output of the RJV (**?**). Indeed, **?**, using firm size as a proxy of absorptive capacity, find empirical support for this variable to increase RJV participation. Other papers, such as **?** for Dutch RJVs and **?** for German cooperations confirm these findings.

R&D

A firm's (cost of) innovation activities is another firm-specific factor that could, in principle, influence its capability to engage successfully in collaborative R&D projects. The idea is that one should have in-house (technological) knowledge to benefit from RJV participation (??). In particular, a strand of literature expects a firm's own engagement in R&D to increase its propensity to engage in R&D cooperation. Empirical evidence on this link, though, is somewhat mixed. For example, ?, ? and ? find that a firm's R&D intensity has indeed a positive and significant impact on the firm's decision to co-operate formally. On the other hand, ?, ? and ? find no evidence that in-house R&D is influencing firms' propensity to cooperate formally with other firms.

Focusing on the cost of doing R&D, ? find that R&D subsidies might lead firms to pool resources in an RJV and hence increase RJV participation. ? also suggest that RJV participation might lead to a pooling of R&D; hence if costs of R&D go up, then RJV participation might become relatively more interesting.

Patent pool

Scholars have abundantly used patent data as a proxy for a firm's stock of knowledge, which in turn can be translated into a firm's capacity to absorb incoming spillovers (e.g. ??). Several studies, such as ? and ?, then argue that this enhanced absorption capacity implies that a firm has more to gain from RJV participation, as it can benefit more from spillovers therein. Both studies find evidence of a positive link between this measure and the likelihood to join an RJV. Related, ? show that firms better capture R&D spillovers from other RJV participants when their capacity to absorb incoming spillovers, through e.g. a larger patent pool, is greater.

Our implementation

Following the literature, we thus include in the RJV participation model several measures of absorptive capacity. First, in terms of firm size, we take the lagged log of sales of the firm as a proxy (Size_{it-1}).[14] Second, in terms of R&D intensity, we take the R&D of a company relative to its capital stock ($\text{R\&D Intensity}_{it-1}$). As an additional (more indirect) measure of R&D, we adapt the logic proposed by BSV who develop instruments for R&D expenditures ($\text{R\&D Cost}_{it-1}$). Firms in our sample are eligible for state-level

[14]For consistency with the previous discussion on the proximity measures and to reduce potential endogeneity issues due to two-way causality, we also lag all proxies for absorptive capacity one period.

R&D tax credits and face different state corporation taxes. When incentivised by the tax system, firms tend to increase their R&D expenses, which in turn might impact RJV participation. Specifically, BSV calculate a state R&D tax price by combining estimates of state-specic R&D tax prices with estimates of the cross-state distribution of rm's R&D. Finally, as a measure of a firm's patent pool, we take a measure of patent stock (Patent Stock$_{it-1}$), where we follow the variable definition proposed by BSV.

3.3. Empirical specification and results

Based on the above discussion, we run the following probit model to estimate the drivers of RJV participation:

$$\begin{aligned} Ins_{it} &= \alpha_0 + \alpha_1 \ln SPILLTECH^{tot}_{it-1} + \alpha_2 \ln SPILLSIC^{tot}_{it-1} \\ &+ \alpha_3 Size_{it-1} + \alpha_4 R\&DIntensity_{it-1} + \alpha_5 R\&DCost_{it-1} \\ &+ \alpha_6 PatentStock_{it-1} + \epsilon_{it}, \end{aligned} \tag{8}$$

where Ins_{it} is a dummy equal to one if firm i is an insider in any RJV at time t. We report the results for the estimation of this probit equation on our main sample of 9,160 observations, i.e., the sample that we use to estimate the main regressions with R&D and Tobin's Q.

[Insert table 2 about here]

The technological spillover pool has a significant and positive impact on RJV participation, as the positive coefficient of $SPILLTECH$ shows. Thus, the incentive to join an RJV increases the larger a firm's total technological spillover. Instead, we do not find a significant relationship between the product market spillover pool and RJV participation (variable $SPILLSIC$). This is perhaps not unexpected, as our literature discussion above showed that the link between the product market space and RJV participation is not that obvious. Furthermore, the coefficients of all proxies for absorptive capacity indicate that a larger absorptive capacity leads to a higher probability of participation: firm size, R&D intensity, and the patent stock positively impact participation, whereas a higher R&D cost has a negative impact.

Our specification, therefore, shows that almost all proposed variables are important drivers of RJV participation.[15] Moreover, the model appears to perform well in terms of fit: the percentage of correct predictions is high and equal to 86%. Thus, we are confident that this equation is a useful auxiliary regression to account for RJV participation in our full model where we assess the impact of the spillovers pools on outcomes, and test how RJV participation mediates this link, while accounting for the fact that RJV participation is endogenous.

4. Effects of RJV participation

Our basic setup is the model of BSV, in which firm performance is affected by knowledge spillovers in the technological space and the business stealing effect in the product market space. We then extend this model and investigate two channels of how RJVs might enhance or mitigate these effects. First, we split the effect of the total spillover pools between RJV-insiders and RJV-outsiders allowing for differential coefficients. This permits us to analyse whether RJV-insiders are generally more able to reap knowledge spillovers and/or to avoid business stealing vis-a-vis RJV-outsiders. Second, we construct additional spillover pools for RJV participants where these additional spillover pools come from other members' R&D in the RJVs. This allows us to investigate if spillovers coming from (other) RJV-insiders are different to those coming from RJV-outsiders. This leads us to the following main specification:

[15] For completeness, in our full model we retain $SPILLSIC$ as an instrument although it is not significant. Dropping it from the model does not alter the results.

$$
\begin{aligned}
\ln Q_{it} &= \beta_1 Out_{it-1} \times \ln SPILLSIC^{tot}_{it-1} + \beta_2 Ins_{it-1} \times \ln SPILLSIC^{tot}_{it-1} \\
&+ \beta_3 Ins_{it-1} \times \ln SPILLSIC^{par}_{it-1} \\
&+ \beta_4 Out_{it-1} \times \ln SPILLTECH^{tot}_{it-1} + \beta_5 Ins_{it-1} \times \ln SPILLTECH^{tot}_{it-1} \\
&+ \beta_6 Ins_{it-1} \times \ln SPILLTECH^{par}_{it-1} \\
&+ \beta_7 Ins_{it-1} + \beta_8 \mathbb{X}_{it-1} + u_{it}, \qquad (9)
\end{aligned}
$$

where Q_{it} is one of the firm performance indicators. Ins_{it-1} and Out_{it-1} are dummy variables, indicating whether firm i is an insider or an outsider, respectively, at time $t-1$, which will be endogenized in the endogenous treatment model discussed below. The matrix $\mathbb{X}_{it-1}$ contains control variables and fixed-effects. Similar as the specification in BSV, it includes a sixth-order Taylor approximation to a firms' R&D stock divided by its assets (see also **?**), industry sales and lagged industry sales, as well as fixed effects for firms and for years. Finally, u_{it} is an error term which is allowed to be heteroskedastic and autocorrelated. In the extended version of this model, where we account for the endogeneity of the RJV participation, additional assumptions on the joint distribution of the error terms are needed and discussed below.

We show two estimations. We first replicate BSV's analysis, where the technology and product market effects are the same for both RJV insiders and outsiders (i.e., we restrict $\beta_1 = \beta_2$, $\beta_4 = \beta_5$ and $\beta_7 = 0$ in equation (9)) and all the RJV-partner specific terms are set to zero ($\beta_3 = \beta_6 = 0$).

We then estimate the full model where we allow for additional effects through RJV participation. First, we allow for a differential effect of the total spillover pools for RJV insiders and outsiders ($\beta_1 \neq \beta_2$, $\beta_4 \neq \beta_5$ and $\beta_7 \neq 0$). We could have chosen a model specification where we estimate the level effect of the spillovers and then look at the additional effect for insiders, where outsiders would be the omitted category. However, we prefer a model that splits the effect of the spillover pools between the insiders and the outsiders and leads to a more direct interpretation of the coefficients' estimates. Our chosen specification is equivalent to estimating the model in the two subsamples, but more efficient.

Second, we allow for a differential effect from the specific RJV partners ($\beta_3 \neq 0$ and $\beta_6 \neq 0$). One can think about these additional spillover pools as an additional interaction effect, which measures the differential impact of the spillover pools of other RJV participants compared to non-participants. These additional spillover variables can by construction only be defined for RJV participants.

4.1. Selection-based endogeneity of RJV participation

As discussed above, participation in an RJV is not a random event. Firm self-select themselves into cooperation agreements due to various reasons. This creates an endogeneity issue that needs to be accounted for empirically. Because of the discrete nature of the participation variable, we therefore implement an endogenous dummy variable (or endogenous treatment) model. Such a model can be applied in situations where a binary-treatment variable partitions the sample population into two sub-samples –as in our case, where a firm is an RJV insider or not– and this partitioning might be endogenous.[16] This model, which is an extension of the endogenous sample selection model proposed by **??**, is a linear potential-outcome model which assumes a specific correlation structure between the unobservables that affect the participation into treatment and the unobservables that affect the potential outcomes.

The model is composed by the outcome equation (9) and an equation for the endogenous treatment (Ins_{it-1}) represented by equation (8) discussed in section 2, lagged one period. The error terms of the two equations, ϵ_{it-1} and u_{it}, are assumed to be distributed as a bivariate normal with mean zero and a given unknown covariance matrix, which is jointly estimated.[17] The model can be either estimated by a two-step maximum likelihood estimator or by a one-step control-function estimator using the generalized method

[16] See **?** for a discussion of self-selection based endogeneity.

[17] For identification, the variance of the error term ϵ_{it-1} is normalized to one, while the variance of the error term u_{it} (σ) as well as the correlation between the two error terms (ρ) are estimated.

of moments with stacked moments (e.g. **?**).[18] An important advantage of this model is that it allows us to account for the endogeneity of the RJV dummy, both when we consider it as a separate variable and in interaction with the technological and product market R&D pools.

For the simple model without RJV participation, we follow BSV and use a Newey-West estimator allowing for autocorrelation of lag 1 in the Tobin's Q, sales and R&D regressions and a negative binomial model for patents.[19]

4.2. Identification

While our framework allows us in principle to account for the endogeneity of RJV participation, our identification strategy hinges mainly on timing. First, in the selection equation, we model that (one period) lagged RJV determinants influence RJV participation. Second, in the outcome equation, we model that (one period) lagged RJV participation –plus other factors– influences the RJV outcomes (R&D and Tobin's Q). Thus, the RJV determinants are lagged twice with respect to the RJV outcomes. Therefore, all variables entering the selection equation are lagged twice with respect to the error term of the outcome equations, u_it.

Our identification strategy hinges then on two assumptions. First, some instruments –$SPILLTECH^{tot}$ and $SPILLSIC^{tot}$ – are excluded through a timing assumption: (i) they enter directly the outcome equations with lag one, (ii) they also enter indirectly the outcome equations –through the participation equation– with lag two. Thus, our identification rests on the assumption that the autocorrelation of the error terms in the main equations is at most of order one. Second, some other instruments such as $Size$,

[18] We implement the *etregress* command in Stata and estimate clustered standard errors at the firm level, which account for heteroskedasticity and autocorrelation. We use the consistent two-step estimator, which is more robust and shows less problems with convergence.

[19] We differ in one important aspect from their estimations, as in our full endogenous treatment model we use one-year lagged instruments for RJV participation as shown in equation (8). Given that RJV participation enters our model lagged one year (Ins_{t-1} in equation (9)), these RJV determinants enter the full model lagged two years. Hence, we lose one year of data compared to BSV. Moreover, in contrast to BSV, we estimate all main regressions in a common sample.

$R\&DIntensity$, $R\&DCost$, and $PatentStock$ are instead fully excluded. We assume, thus, that they do not directly enter the outcome equations.

Both above-mentioned assumptions are not really testable. Therefore, in a robustness check reported in Appendix A, we estimate a model where we include all instruments in the outcome equations with lag one, as we do for the spillover variables. Thus, identification comes through the timing assumption, by maintaining the exclusion restriction that their second lag does not enter the outcome equations directly (no autocorrelation of order higher than one for u_{it}). We discuss in detail in Appendix A these results, but the qualitative results concerning the key spillover variables, $SPILLTECH$ and $SPILLSIC$, and their interactions, are robust to this alternative identification strategy.

4.3. Empirical Results

We focus on R&D and market value (Tobin's Q) as key firm-performance indicators. The underlying logic is that R&D is the innovation input, and Tobin's Q the final outcome of the innovation process.

First off, it is worth noting that the endogeneity of RJV participation is an important issue to account for, as can be seen in the endogenous treatment models reported in columns (2) and (4) in table 3. The relevant statistic to assess the potential endogeneity is the correlation (ρ) between the error terms in the RJV participation equation (8) and the outcome equation (9). In the two-step approach that we adopt, estimates for ρ are only obtained indirectly. First, we augment the regression equation (9) with the hazard rate – or inverse Mill's ratio – from the probit estimation, which is defined as the ratio of the probability density function and the complementary cumulative distribution function. The coefficient estimate for the hazard (λ), is the product of ρ and the variance of the error term in the outcome equation (σ).[20] The parameter λ is negative in both models but only significant in the Tobin's Q equation. This negative effect is driven by a negative correlation ρ between the two error terms. This correlation measures the extent

[20]A consistent estimate of the regression disturbance variance σ is obtained using the residuals from the augmented regression and the parameter estimate on the hazard, and the estimate $\hat{\rho}$ is then $\frac{\hat{\lambda}}{\hat{\sigma}}$.

of the endogeneity of RJV participation and indicates that unobservables that increase the outcome at the same time lower the probability of RJV participation, particularly for Tobin's Q.

Second, we see that RJV participation (Ins) has *no* direct effect on a firm's R&D spending and resulting Tobin's Q., i.e., the coefficient estimates for this variable in columns (2) and (4) in table 3 are not significant. This non-significant impact is interesting, we believe, in its own right: all effects of RJV participation arrive through the channel of spillover pools. We now turn to the discussion of the spillover variables, where we first explain results on the product market space and then on the technology space.

[Insert table 3 about here]

Product market space

We first focus on the effects of the R&D of companies that are close in the product market space. The estimated coefficient of $lnSPILLSIC^{tot}$ for the R&D equation in column (1) suggests that firms react positively to the R&D from product market competitors, although the effect is not significant. Furthermore, as shown in column (2), this is true independent of whether the focal firm participates in a RJV or not, as the interaction terms of $lnSPILLSIC^{tot}$ with the insider and outsider dummies are both positive and insignificant.

The coefficient of $lnSPILLSIC^{tot}$ estimated in column (3) suggests that Tobin's Q is negatively and significantly affected by an increase in the R&D of product market rivals. The rationale for this finding could be the following: increased R&D of product market rivals reduces their cost of production (or increase the value of their products), thereby increasing their relative competitive advantage. This, in turn, reduces the focal firm's profit margin or market share, thus reducing its value. This is the so-called business stealing effect (see e.g., **?**).

Column (4) shows that this is true both for firms participating in RJVs, as well as for firms that do not do so, as the interactions of $lnSPILLSIC^{tot}$ with the insider and outsider dummies are both negative and significant. Notice, though, that the interaction coefficient is smaller in absolute terms for RJV insiders than for outsiders, and the difference between these two coefficients is significant at the 1% level. This is consistent with the view that participating in RJVs makes firms "more resilient." That is, RJV participants are more able to shelter from the negative effects of product market competition; in particular, they are less negatively affected by the business stealing arising from an increase in the R&D of product market competitors.

RJV participation, though, opens up a different spillover channel: the (interacted) variable $Ins \times lnSPILLSIC^{par}$ has a negative and significant impact on the focal firm's R&D (column (2)) and, at the same time, a positive effect on the focal firm's value (column (4)).[21] This suggests that participating in the same RJV as a product market competitor allows the focal firm to reduce its R&D expenditures in the face of an increase in the R&D of this RJV-participating product market competitor, and that this provides additional benefits for the focal firm.

These findings are consistent with the idea that the focal firm can economise on R&D costs through the R&D of competitors that are also RJV participants. This coordination of R&D among RJV participants can be due to a reduction of wasteful duplication, which is positive from a welfare point of view. Alternatively, it may be the case that RJV participants suppress otherwise healthy R&D competition, i.e., collude in R&D, thereby providing too little R&D from a social point of view (in our setting we cannot distinguish between these two rationales). In any case, the combination of RJV participants benefiting from the R&D of others and at the same time reducing their own R&D, in turn, has a positive impact on a focal firm's value. The beneficial reduction of R&D suggests that RJVs among product market competitors are able to eliminate duplication of R&D efforts (**?**).

[21]Note that these coefficients should be interpreted as interactions that capture the differential effect of the R&D of the RJV's partners, compared to that of non-RJV partners. Thus the overall effect of the R&D of competitors for RJV partners can be seen as the sum of the coefficients' estimates for $SPILLSIC^{tot}$ and $SPILLSIC^{par}$. This sum is still negative, but less negative than the effect of competitors that are not RJV partners.

Technology space

We now turn to the effect of the technological spillovers. In column (1) we see that the impact of the spillover variable, $lnSPILLTECH^{tot}$, on the R&D of the focal firm is negative, although not significantly so. In column (2), when we interact the spillover variable with the dummies for outsider and insider, we find that both coefficients' estimates stay negative. Yet, only the latter, i.e., the spillover effect for the insiders, $Ins \times lnSPILLTECH^{tot}$, has a (marginally) significant impact. Thus, we find that a focal firm's R&D is a strategic substitute with respect to the R&D of technologically close companies, but only when that focal firm is an RJV insider.

This indicates that RJV participants are better equipped to absorb the R&D of technologically close companies, and thus can reduce their own R&D in response. RJV participation is, therefore, an enabler for the absorption of incoming technological spillovers. The difference in the degree of absorption between insiders and outsiders is also translated into a different impact on Tobin's Q. The R&D of technologically close companies has a larger impact on RJV insiders than on outsiders, as the coefficients on $Out \times lnSPILLTECH^{tot}$ and $Ins \times lnSPILLTECH^{tot}$ indicate in column (4).

Finally, the (interacted) variable $Ins \times lnSPILLTECH^{par}$ has a positive and significant impact on the focal's firm R&D, as can be seen in column (2).[22] Column (4) shows that $Ins \times lnSPILLTECH^{par}$ in turn has a negative and significant impact on the focal's firm Tobin's Q (where the sum of the coefficients of $Ins \times lnSPILLTECH^{tot}$ and $Ins \times lnSPILLTECH^{par}$ is still positive).

Interestingly, this indicates that there is a relatively too high R&D investment among technologically close RJV partners. Indeed, the reduction of R&D investment, thanks to the absorption of technological spillovers, is lower among RJV partners than among non-RJV partners. The relative over-investment may be because of the fact that the appropriability of joint R&D is lower within RJVs (?). Overall though, RJV participation

[22] As above, this coefficient estimate is an interaction effect and the overall effect of R&D technological spillovers of RJV partners can be seen as the sum of the coefficients of $Ins \times lnSPILLTECH^{tot}$ and $Ins \times lnSPILLTECH^{par}$. The sum is still negative which means that the R&D of the focal firm is still reduced.

leads to benefits in the technology space too, as the positive effects on firm value of increased absorption of technology spillovers outweigh the negative effects of too much R&D investment.

5. Conclusion

This paper assesses if and to what extent firms' collaboration through RJVs constitutes a mechanism that mediates the effect of technology as well as product market spillovers on a firm's R&D and Tobin's Q. We build on the framework proposed by **?** and propose a more flexible model that includes RJV participation. Since the choice to join an RJV is endogenous, we first analyze the determinants of participation. The outcome and RJV participation equations are then jointly estimated in an endogenous treatment regression model.

Our analysis applies this framework to the RJVs created under the auspices of the U.S. NCRA program that started in 1984, which stimulates large scale inter-firm cooperation agreements in basic research and pre-competitive R&D. These large RJVs were specifically created with the goal of generating and internalizing knowledge spillovers. Because of the broad nature of the NCRA program, many firms across several industries entered in RJVs and their participation status often changes over time. Therefore, the NCRA program provides an excellent empirical setting to investigate the interaction between technological, as well as product market spillovers, and RJV participation.

We analyze two ways through which RJVs might enhance or mitigate spillovers. First, the spillover effects may be different for RJV insiders and outsiders. Participating in RJVs increases firms' capabilities, for instance in terms of absorptive capacity. Second, the R&D pool of a focal firm's RJV partners might have a differential impact, compared to that of the R&D of non-partners, on the R&D and Tobin's Q of the focal firm.

Our results underscore the benefits of RJV participation in mitigating negative product market effects and enhancing positive technology spillovers. The gains in the product market space are two-fold. First, participating in RJVs makes firms "more resilient," that is, more able to shelter from the negative effects of product market competition, and in particular from the business stealing effect arising from an increase in the R&D of product market competitors. In addition, participating in the same RJV as a product market competitor allows a focal firm to reduce its R&D expenditures in the face of an increase in the R&D of the product market competitor, and this provides additional benefits for the focal firm.

In the technology space, we find evidence that indicates, first, that RJV insiders are better equipped to absorb technology spillovers. RJV participants can reduce their own R&D more in response to an increase in the R&D of technologically close companies, leading to a higher firm value. On the other hand, RJV participation leads to relatively too much R&D investment among technologically close participants. Overall though, RJV participation leads to benefits in the technology space too, as the positive effects on firm value due to increased absorption outweigh the negative effects of a too high investment in R&D.

The innovation literature has long recognized that firms' innovation cooperation within RJVs is one of the most important channels through which firms can appropriate the returns from R&D. By confirming this intuition, our analysis implements the perhaps most natural step to answer BSV's call to investigate how mechanisms of knowledge transfer might shape both technology and product market spillovers. This might be particularly useful as it can further help discussing and analyzing the impact of policies that are specifically implemented to support R&D.

More research on the topic would be helpful. Whereas the NCRA program provides for the ideal setting to investigate the impact of RJV participation on spillovers, the program was established in U.S. industries with a focus on large research cooperations in the 1990s. It would be important to see to which extent our conclusions hold in other settings. Furthermore, the main focus of this paper is on R&D as main input and firm value as final outcome of the innovation process. Datasets containing information on outcomes such as productivity and product innovations could be an improvement. Related, a more precise measurement of innovation output than a company's set of patents and a more precise measurement of product markets than sector codes could shed new light on the important topic of spillovers.

6. Tables

Table 1: Summary statistics

	Mean	Median	SD	Obs
R&D	111.25	5.00	495.20	9160
Tobins Q	2.46	1.50	3.06	9160
Cite-weighted patents	113.04	2.00	589.76	8606
Sales	3445.18	563.00	10660.29	9160
SIC spillovers	1339.40	371.93	2160.21	9160
TEC spillovers	4721.26	3769.88	3772.35	9160
SIC spillovers insider	105.87	0.00	477.85	9160
TEC spillovers insider	360.80	0.00	1238.89	9160
Market value	4623.80	496.52	18082.63	9160
R&D Stock	645.60	33.52	2860.87	9160
Total assets	4724.92	452.31	20351.82	9160
Employees	18.16	3.84	52.81	9086
Patent count	18.51	1.00	86.87	9160
R&D tax incentive	0.20	0.18	0.07	9160
R&D intensity	0.48	0.19	0.89	9160

Notes: Table reports mean, median, as well as the standard deviation. Monetary values are in million 1996 USD.

Table 2: Determinants of participation

	Coeff. Estimates	St. Errors
$\ln SPILLTECH^{tot}_{it-1}$	0.262***	(0.03)
$\ln SPILLSIC^{tot}_{it-1}$	0.013	(0.01)
ln Sales$_{it-1}$	0.160***	(0.01)
R&D Intensity$_{it-1}$	0.069***	(0.02)
R&D Cost$_{it-1}$	-2.646***	(0.29)
Patent Stock$_{it-1}$	0.122***	(0.01)
Observations	9160	
Correctly classified	85.2%	

Notes: Standard errors in parentheses are robust to heteroskedasticity.

Table 3: Spillover effects on R&D and Tobin's Q

	R&D		Tobin's Q	
	(1)	(2)	(3)	(4)
$\ln SPILLSIC^{tot}_{it-1}$	0.015		-0.073**	
	(0.08)		(0.03)	
$Out_{it-1} \times \ln SPILLSIC^{tot}_{it-1}$		0.005		-0.087***
		(0.04)		(0.03)
$Ins_{it-1} \times \ln SPILLSIC^{tot}_{it-1}$		0.064		-0.057**
		(0.05)		(0.03)
$Ins_{it-1} \times \ln SPILLSIC^{par}_{it-1}$		-0.040***		0.016**
		(0.01)		(0.01)
$\ln SPILLTECH^{tot}_{it-1}$	-0.189		0.377***	
	(0.16)		(0.13)	
$Out_{it-1} \times \ln SPILLTECH^{tot}_{it-1}$		-0.218		0.255***
		(0.14)		(0.09)
$Ins_{it-1} \times \ln SPILLTECH^{tot}_{it-1}$		-0.276*		0.324***
		(0.16)		(0.10)
$Ins_{it-1} \times \ln SPILLTECH^{par}_{it-1}$		0.071**		-0.027*
		(0.03)		(0.02)
Ins_{it-1}		-0.084		0.145
		(0.87)		(0.50)
Hazard				
λ		-0.072		-0.479**
		(0.150)		(0.091)
σ		0.759		0.541
ρ		-0.095		-0.885
Observations	9160	9160	9160	9160
Firm fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓

Notes: Standard errors in parentheses are robust to heteroskedasticity. Column (1) and (3) are replications of **?** model; column (2) and (4) allow for differential slopes and constants between members and non-members and allow for an additional effect from partners' spillovers controlling for endogenous selection into RJVs. We do not report the estimates for the probit as they are identical to those reported in table 2. All specifications contain fixed-effects at the firm and year levels as well a sixth-order Taylor approximation to a firms' R&D stock divided by its assets (see also **?**), industry sales and lagged industry sales.

A. Appendix

We briefly discuss here the results obtained with an alternative identification strategy. In the model reported here, we assume that all variables that determine RJV participation also affect RJV outcomes. In all equations, the right-hand side variables are lagged once. Hence, because of our modelling that outcomes depend on the lagged values of RJV participation, all variables determining participation are effectively lagged twice with respect to the error term in the outcome equations u_{it}. Thus, our identification here fully rests on the assumption that the autocorrelation of the error terms in the main equations is at most of order one.

The qualitative results concerning the key spillover variables, $SPILLTECH$ and $SPILLSIC$, and their interactions, are robust to this alternative identification strategy. In terms of sign, all results are the same. In terms of significance, the 'new' R&D equation yields slightly more significant results than our main specification. Results for the Tobin's Q equation are virtually identical.

Concerning the additional variables that we add to the outcome equations in the alternative identification strategy –lag one of *R&DIntensity*, *R&DCost*, *PatentStock*, *Size*– they are only marginally significant in the R&D equation, while they are more significant in the Tobin's Q equation. Specifically, in the R&D equation, only our measure of size (Sales) is negative and significant. We interpret this as an indication that, conditional on RJV participation, these variables (except Size) could in principle be excluded from the R&D equation, which is close to our main specification.

In the Tobin's Q equation, instead, several of these additional variables are significant. Yet, the coefficient estimates for the spillover variables (and their interactions) are not affected. This would suggest that, conditional on controlling for RJV participation, these additional variables are almost orthogonal to the spillover variables. One could interpret this as well as supporting our preferred specification in the main text.

Table 4: Spillover effects on R&D and Tobin's Q - alternative identification strategy

	R&D		Tobin's q	
	(1)	(2)	(3)	(4)
$\ln SPILLSIC^{tot}_{it-1}$	0.015		-0.073**	
	(0.08)		(0.03)	
$Out_{it-1} \times \ln SPILLSIC^{tot}_{it-1}$		0.046		-0.082***
		(0.04)		(0.03)
$Ins_{it-1} \times \ln SPILLSIC^{tot}_{it-1}$		0.102**		-0.051*
		(0.04)		(0.03)
$Ins_{it-1} \times \ln SPILLSIC^{par}_{it-1}$		-0.030***		0.016**
		(0.01)		(0.01)
$\ln SPILLTECH^{tot}_{it-1}$	-0.189		0.377***	
	(0.16)		(0.13)	
$Out_{it-1} \times \ln SPILLTECH^{tot}_{it-1}$		-0.491***		0.229**
		(0.13)		(0.10)
$Ins_{it-1} \times \ln SPILLTECH^{tot}_{it-1}$		-0.615***		0.250**
		(0.15)		(0.11)
$Ins_{it-1} \times \ln SPILLTECH^{par}_{it-1}$		0.047**		-0.030*
		(0.03)		(0.01)
$R\&DIntensity_{it-1}$		0.013		1.003***
		(0.23)		(0.17)
$R\&DCost_{it-1}$		-0.009		-0.058
		(0.58)		(0.43)
$PatentStock_{it-1}$		-1.042		-5.047***
		(0.82)		(0.54)
$lnSales_{it-1}$		-0.249***		-0.124***
		(0.03)		(0.02)
Ins_{it-1}		-1.245		1.059*
		(0.87)		(0.56)
Hazard				
λ		-0.352		-0.701
		(0.150)		(0.107)
σ		0.724		0.621
ρ		-0.486		-1.000
Observations	9160	9160	9160	9160
Firm fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓

Notes: Standard errors in parentheses are robust to heteroskedasticity. Column (1) and (3) are replications of **?** model; column (2) and (4) allow for differential slopes and constants between members and non-members and allow for an additional effect from partners' spillovers controlling for endogenous selection into RJVs. We do not report the estimates for the probit as they are identical to those reported in table 2. All specifications contain fixed-effects at the firm and year levels as well a sixth-order Taylor approximation to a firms' R&D stock divided by its assets (see also **?**), industry sales and lagged industry sales.