Research Joint Ventures in an R&D Driven Market with Evolving Consumer Preferences:

An Evolutionary Multi-Agent Based Modeling Approach

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Abstract. R&D collaborations have increasingly attracted the attention of both academic and business circles in the last couple of decades. Several empirical studies have concentrated on the firms' incentives to participate in these collaborations. This paper presents an alternative approach to R&D collaborations using an evolutionary, multi-agent based and sector-level R&D model. The model simulates the evolution of an R&D driven market composed of profit-driven firms and boundedly rational consumers to explore frequently discussed research questions in the relevant empirical literature. This modeling exercise will extend beyond a basic confirmation/rejection of these research questions by showing that the way a firm is defined as an R&D collaborator has significant effects on research results. A clear inference based on these outcomes is that the research results of the empirical studies on research joint ventures should be interpreted with some caution in regard to the chosen method of defining collaborator firms.

Keywords: R&D collaborations; industrial dynamics; evolutionary economics; agent-based modeling

1. Introduction

Firms heavily depend on improved products to survive in competitive markets. A continuous introduction of new products necessitates both specialized and diverse types of knowledge, which is almost often beyond the limits of the accumulated knowledge within the boundaries of a single firm (Cowan et al. 2006). Hence, firms turn to the market to find what they look for, but due to its tacitness, knowledge is hard to acquire in the market. Tacitness, of course, inhibits imitation - which preserves innovation incentives - but it also prevents a deliberate and intentional market based transferring of knowledge (Mowery et al.1998). That is why firms collaborate in R&D partnerships on a reciprocal basis to share knowledge (Morone and Taylor 2012). R&D partnerships are part of a relatively large and diverse group of inter-firm relationships that one finds in between standard market transactions of unrelated companies and full integration by means of mergers and acquisitions (Hagedoorn 2002).

Alongside monetary funding, the contribution of an individual firm to an R&D partnership involves sharing of human capital, accumulated knowledge embedded in firm-specific factors, and access to information and activities within its own R&D division. Firms are not merely technological entities but are rather complex conglomerations of human capital and knowledge accumulated through past learning. Learning and R&D activities are historically path-dependent and they generate firm-specific human capital, knowledge, and R&D resources which create divergence in knowledge and expertise of different firms, which are often likely to be complementary. Firms form alliances to share these resources and to boost their R&D productivity with the help of knowledge complementarities. In these alliances, technological overlap as a basis of a common technological understanding, reciprocity as a prerequisite for knowledge exchange, and the expected value of a research cooperation are the major determinants (Cantner and Meder 2006).

This study explores three research questions frequently studied in research joint venture (RJV) literature. The first question is whether R&D collaborators command a higher market share than non-collaborators. The second question is what kind of a relationship there is between competition level and the market share of R&D collaborators. The last research question is whether higher capability heterogeneity among firms means higher market share of collaborators motivated by knowledge sharing. To answer these questions, an evolutionary, multi-agent based, sector-level innovation model is designed to simulate the dynamics of an R&D driven sector. First, this model will be used to analyze the interaction between R&D activities of firms and differentiated consumer preferences in structuring the evolution of an industry. Then, we will explore our research questions regarding R&D collaborations within this context and the reader will observe that how one differentiates between collaborators and non-collaborators has a significant effect on the answers.

An apparent advantage of a simulation analysis in comparison to an empirical one in the context of this study is that the observer can effortlessly keep track of all variables of interest and observe whether a firm showing the characteristic of being a collaborator is actually collaborating at a given point in time. As will be clear in the following, this discrepancy may have significant consequences for the research results. Hence, we observe that the empirical findings in the relevant literature may be driven by the way a firm is defined as an R&D collaborator. Another advantage of a simulation analysis over empirical studies in the context of this line of research is the opportunity to conduct controlled experiments to answer research questions like, ceteris paribus, how competition level and capability heterogeneity affects the market share of R&D collaborators and knowledge sharing R&D collaborators, respectively. This and many other uses of agent-based modelling in overcoming the constraints of empirical methods are explicitly discussed in Garcia (2005). It also helps us to understand the underlying mechanisms that explain why certain results occur the way they do. There are also a few advantages of this evolutionary model over the alternative ones in the relevant literature. To begin with, it is one of the few models studying RJVs with different motives (cost sharing vs. knowledge sharing) from an agent-based perspective. Secondly, whereas most evolutionary models focus on process innovation, this one exclusively models product innovation, i.e. technical progress is embodied in products. The third is that firms compete both in the R&D process and goods market rather than in any one of them. Lastly, rather than single-product firms, the market is populated with multi-product firms which can serve to different niches of consumers concurrently. With the continuous introduction of new innovations, products transform from undiscovered to discovered and then from cutting edge product to obsolete. As the product space steadily shifts, the consumers are compelled to redefine their product choices within the given product range.

The rest of the paper is organized as follows: The next section presents the pseudo-code of the model. In section 'Simulation Experiments', the results of the simulation analyses are discussed. The last section concludes.

2. The Pseudo-Code of the Model

At the initialization period, market is populated with N firms each endowed with an R&D strategy (50/50 probability of being a collaborator or a non-collaborator and an innovator or an imitator, and 50/50 probability of being a knowledge-sharing or cost-sharing collaborator), a random R&D technique, and a product portfolio. Also, each consumer is assigned to an ideal product profile. The routine for the rest of the simulation is implemented as follows:

1. Firms set a price for each product as a function of profits from that product in the previous periods.
2. Firms make marketing expenses for each product as a function of the quality of that product.
3. Each consumer determines her ideal product.
4. Consumers sample a few random products, structure their memory sets and purchase the best product within this set.
5. Products with an average market share below a threshold level are deleted from the market. Firms with no products to sell leave the market. New firms with random strategies enter.
6. In accordance with their R&D strategies, firms either choose to perform R&D on their own or form RJVs.
7. Each firm and RJV either innovates or imitates.

3. Simulation Experiments

This section includes the results of a series of simple simulation experiments designed to answer our research questions[1]. The analysis in this section is based on the end of simulation values of variables for 100 simulation runs each with a different seed value. The firms follow one of six exclusive strategies: non-collaborator innovators, non-collaborator imitators, cost-sharing collaborator innovators, knowledge-sharing collaborator innovators, cost-sharing collaborator imitators, and knowledge-sharing collaborator imitators.

We start with our first question whether collaborators command a higher market share than non-collaborators. Being in collaboration involves a trade-off. The R&D efficiency of joint R&D projects can be higher (especially for firms motivated by technology sharing) than that of firms working in isolation due to knowledge complementarities. Besides, collaborators pool their R&D resources to succeed in R&D projects that no other firm can do in isolation. The downside of being in collaboration is that they need to share the end result of the R&D projects, which makes the partners compete against each other in the same product markets and R&D race. The distribution of the end of simulation value of the market share of collaborator firms is drawn as a box plot in Figure 1 with two different calculation methods for the very same simulation run. In the first case (active collaborators) a firm is regarded to be a collaborator at a given period only if it is in collaboration at that specific period. In the second case (potential collaborators) a firm is always regarded as a collaborator if it shows the characteristic of being a collaborator by trying to collaborate with a partner every period. Therefore, potential collaborators include all active collaborators together with the firms who failed in partnering although they tried. The mean values for active and potential ones are 34% and 56%, respectively. To test our research question, one needs to observe if the average market share of collaborator firms is significantly higher than 50% and since the average market share for active collaborators is way lower than this value, this analysis will be performed only for potential collaborators using a one-sided t-test. However, the t-test requires the sample follow a normal distribution. To test for the normality of this sample, the Jarque-Bera test is performed. The test result shows that the null hypothesis that the sample comes from a normal distribution cannot be rejected[2]. Now that it can be safely assumed that our sample comes from a normal distribution, a one-sided t-test can be performed. The null hypothesis that the mean is not bigger than 50 is rejected. Hence, we can argue that on average collaborators command a higher market share than non-collaborators. This simulation exercise makes it possible to collect data both on potential and active collaborators and exemplifies how the way one differentiates between collaborators and non-collaborators produces opposite results to the very same research question. In empirical studies researchers do generally not have a chance to make such a distinction.

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[1] The results of the sensitivity analysis confirm that simulation experiment results are robust to changes in market size and R&D intensity.

[2] All statistical tests in this section are performed at 5% significance level

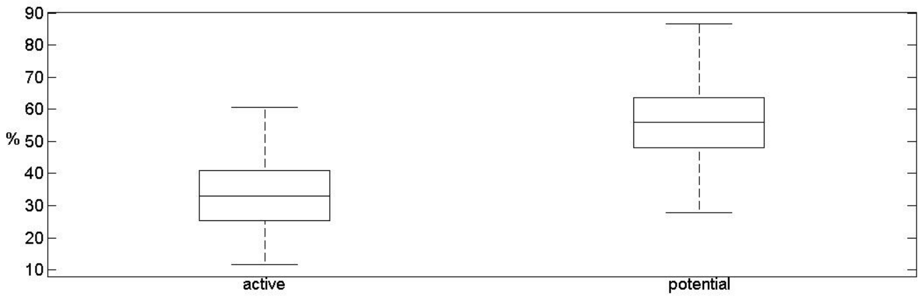

Fig. 1. The market share (%) of active and potential collaborator firms

Our second question was what kind of a relationship there is between competition level and market share of collaborators. Figure 2 shows how the market share of active collaborators is conditioned by the level of competition which is proxied with the number of new entrants every period. A closer examination of the simulation data reveals that there is a strong positive and linear relationship between the number of entries and the level of competition which is measured by the Herfindahl index. The box plot for the distribution of the end of simulation value of the market share of collaborators is drawn for the cases when the level of competition is low, medium and large with median values of 19%, 33% and 39%, respectively. This figure is a vivid example of how competition can increase the efficiency of R&D collaborations through economies of scale and elimination of duplication of efforts. Sharing costs and pooling knowledge made it possible for the collaborators to undertake costly R&D projects that none would undertake alone in a highly competitive environment. A hypothesis test can be performed to support this graphical analysis with a statistical one. The normality of the sample distributions should be checked first to determine the type of the hypothesis test. The Jarque-Bera test results show that only when the level of competition is low, the sample does not follow a normal distribution. Therefore, Wilcoxon rank sum and t-test will be used to test the null hypothesis that competition does not positively affect the market share of active collaborators. The hypothesis test results complement our graphical analysis; the mean value when competition is high is statistically significantly higher than the mean value when it is medium and the median value when it is medium is statistically significantly higher than the median value when it is low. Therefore, our hypothesis is rejected.

Repeating this simulation analysis with an alternative approach to collecting data on the market share of collaborator firms leads to strikingly diverse results. At this point it should be stated that in the previous case at a given moment a firm is regarded as a collaborator only if it participates in a RJV at that specific moment. Alternatively, Figure 3 depicts the distribution of the end of simulation value of the market share of collaborators when a firm is counted always as a collaborator if it engages in R&D partnership activities independent of the outcome which might be a success or failure in finding a partner. This is the only difference between these two cases. Competition this time negatively affects collaborator firms. A possible explanation might be the negative effect of having to share the fruits of RJVs -turning a research partner directly into a competitor- which is emphasized especially when competition is already high due to a high number of new entrants every period. The median values are 80%, 56% and 53% when competition is low, medium and high, respectively. The normality test again shows that only when the level of competition is low, the sample does not follow a normal distribution which requires one to use non-parametric Wilcoxon rank sum and t-test test to investigate the null hypothesis that competition level does not negatively affect the market share of potential R&D collaborators. The test results conclude that the median value when competition is low is statistically significantly higher than the median value when competition is moderate and the mean value when competition is moderate is higher than the mean value when competition is high. Therefore, the research hypothesis is rejected also using this alternative approach, but this time the direction of the relationship between competition and the market share of collaborators is opposite to the previous case and this relationship is again statistically significant. This discrepancy in the analysis results necessitates a deeper examination and the simulation model provides us the required simulation data for this next step. A possible explanation may lie in how the ratio of the number of active collaborators to the number of potential ones is conditioned by the level of competition. Figure 4 gives this collaboration ratio in time for three different levels of competition and it confirms our expectation. The ratio is higher when competition is high than when it is medium and it is much higher when it is medium than when it is low. This is due to the fact that the level of competition is positively related with the number of new entrants each period. When there is a larger pool of potential partners, it is more likely for a firm to collaborate with another following the same R&D strategy and planning to invest in a similar technology. That collaboration ratio increases in competition explains how potential collaborators can lose their market share whereas active collaborators increase theirs as competition intensifies. Hence with the help of our simulation model we conclude that the underlying mechanism behind diverse results regarding the effect of competition on the market share of collaborators in two different cases is how collaboration ratio is determined by the level of competition.

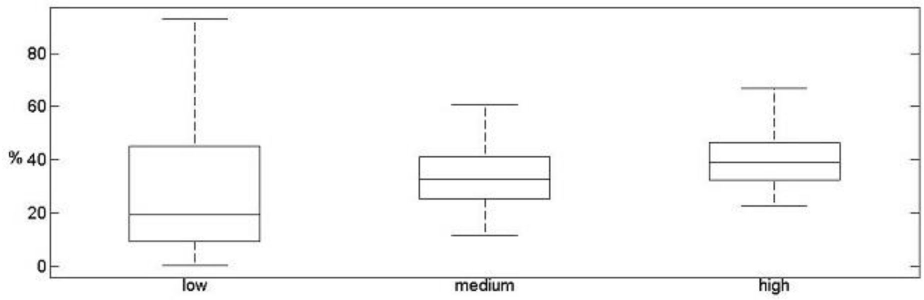

Fig. 2. The market share (%) of active collaborator firms when the level of competition is low, medium and high

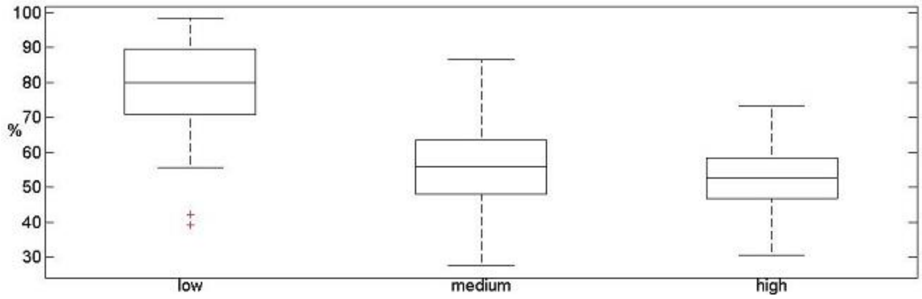

Fig. 3. The market share (%) of potential collaborator firms when the level of competition is low, medium and high

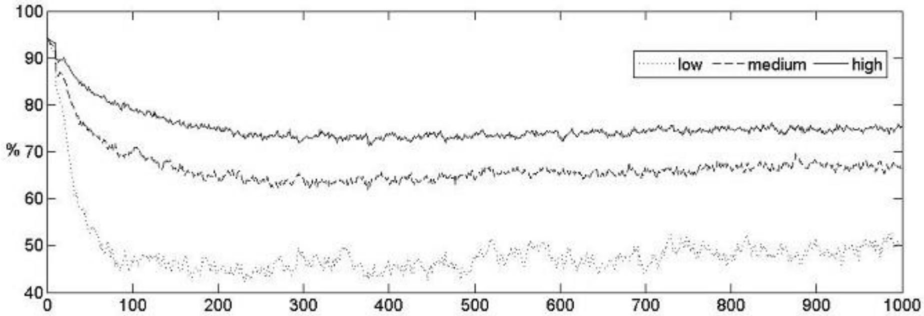

Fig. 4. Collaboration ratio (%) when competition is low, medium and high

In the RJV literature, it is claimed that the relative importance of the skill-sharing motive in R&D consortia increases with heterogeneous capabilities (Sakakibara 1997). Heterogeneous capabilities increase the possibility that two firms joining for an R&D process possess complementary knowledge enhancing their innovative productivity. Capability heterogeneity is defined here as the breadth or diversity of technological capabilities that firms command. Furthermore, Anbarci et al. (2002) claimed that if complementarity is extremely low, RJVs can further lead to lower profits and social welfare as well. Figure 5 is drawn to explore these claims and shows how the market share of technology motivated active collaborators is affected by the overall capability heterogeneity in the firm population. The distributions for the end of simulation value of the market share of collaborators motivated with technology sharing are given as a box plot when knowledge heterogeneity is low, medium, and high with median values of 1%, 14%, and 16%, respectively. As suggested by Anbarci et al. (2002), when capability heterogeneity and hence technology complementarity is too low, the market is dominated by the non-collaborators. Starting from this highly disadvantageous point for the collaborators, they increase their market share with an increase in capability heterogeneity. As stated before, this is because a higher level of heterogeneity makes it more likely for a firm to partner another firm which is at optimum distance from itself in the technique space and this boosts knowledge complementarity and hence R&D

productivity of this alliance over that of a firm doing R&D in isolation. Further increases in knowledge heterogeneity do not bring about a higher market share for technology collaborators. The reason is that population knowledge heterogeneity levels beyond an optimum point do not boost the possibility that any two firms in optimum distance from each other in technique space form an alliance. Therefore, beyond an optimum value, further increases in knowledge heterogeneity do not increase average R&D productivity. This graphical analysis should be supplemented with a statistical one. Using Jarque-Bera test, it is concluded that the samples do not come from normal distributions. Hence, Wilcoxon rank sum test is performed to see whether the market share of knowledge-sharing active collaborators increases with knowledge heterogeneity. The test results show that the median value for a low level of knowledge heterogeneity is significantly lower than the median value for a medium level, which in turn is not statistically significantly different than it is when the knowledge heterogeneity is high. These results support the graphical analysis.

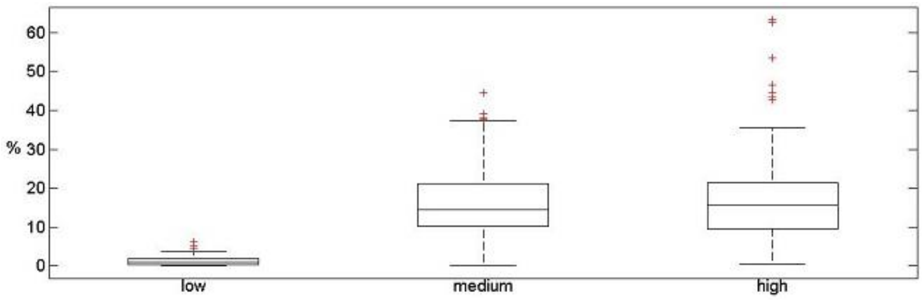

Fig. 5. The market share (%) of knowledge-sharing active collaborators when knowledge het erogeneity is low, medium or high

The effect of knowledge heterogeneity can also be tested for knowledge-sharing potential collaborators. A box plot for the distribution of the end of simulation value of the market share of knowledge-sharing potential collaborators for different level of knowledge heterogeneity can be observed in Figure 6. It is very similar to Figure 5 supporting the argument that knowledge heterogeneity does its job on knowledge-sharing active collaborators through its effect on knowledge-sharing potential collaborators. This graphical explanation can be confirmed with a statistical test. Jarque-Bera test shows that only when heterogeneity is low, the sample does not come from a normal distribution. In order to test whether there is a statistically significant difference between the median values and means of the samples, Wilcoxon rank sum and t-test is used. The median value for a low level of knowledge heterogeneity is significantly lower than the median value for a medium level and the mean value for a medium level is significantly lower than it is when the knowledge heterogeneity is high. Hence the graphical explanation is statistically confirmed.

For a complete analysis one should also explore collaboration ratio within knowledge-sharing potential collaborators as a function of knowledge heterogeneity.

Figure 7 below is drawn for this purpose. Collaboration ratios take on very similar values for medium and high levels of knowledge heterogeneity, which is in congruence with the fact that the market shares of knowledge-sharing collaborators are very close at these knowledge heterogeneity levels. However, a comparatively higher collaboration ratio does not go along with low market shares of knowledge-sharing collaborators when knowledge heterogeneity is low. Limited knowledge heterogeneity suppresses technological progress and hence product diversification among RJVs increasing the likelihood for a potential R&D collaborator to find a partner planning to invest in a similar product. Hence the simulation model enables us to observe that the reason for the low market share of knowledge-sharing active collaborators in this case is the low market share of knowledge-sharing potential collaborators.

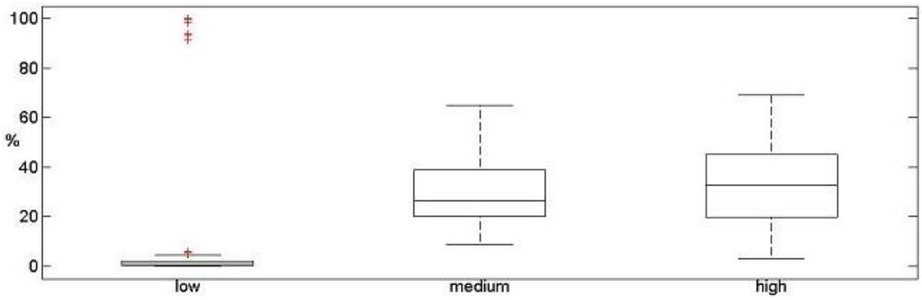

Fig. 6. The market share (%) of knowledge-sharing potential collaborators when knowledge complementarity is low, medium or high

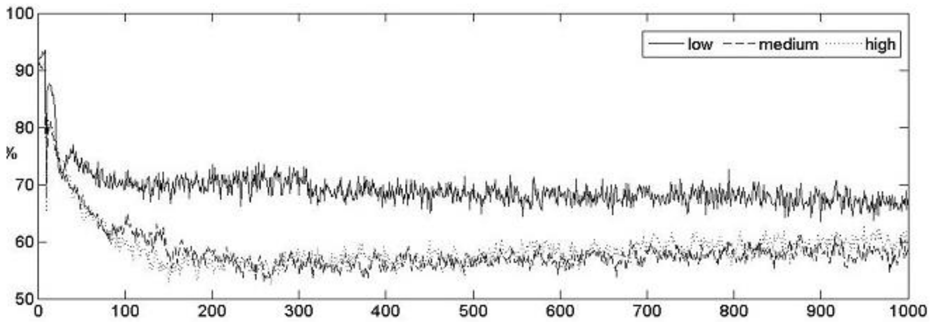

Fig. 7. Collaboration ratio (%) within knowledge-sharing potential collaborators when knowledge complementarity is low, medium or high

4. Conclusion

Although R&D partnership is the least expected form of collaboration since knowledge creation is a core competence of a firm, we have observed acceleration in the number of such partnerships in the past few decades. This phenomenon has motivated economists to study the incentives of firms to collaborate in R&D and the effects of these collaborations on firms with different incentives. This study is a contribution to the discussion of the frequently encountered research questions in this literature and to furthering the understanding of the reasons behind the research results with the help of an agent-based model.

The agent-based model simulates the working of an R&D driven market with both supply and demand side. Firms compete both in goods market and R&D process and consumers act to maximize their utility with their product choices that fit their preferences best. The interaction between supply and demand results in technological progress that continuously renews technology portfolios of firms and product choices of consumers. Firms achieve technological progress either via innovation or imitation and either in a RJV or in isolation.

The simulation model used in this study allowed us to draw a distinction between active and potential collaborators, which is harder to make in empirical studies. A firm is an active collaborator only if it succeeds in forging an alliance whereas it is sufficient to search for a partner to be counted as a potential collaborator. The first conclusion of the paper is that active R&D collaborators command a lower market share than non-collaborators. In other words, the disadvantage of creating your own competitor in the goods market and R&D race by sharing the end results of the R&D projects outweighs the advantages of pooling R&D budgets and knowledge complementarities on the part of collaborators. An alternative look into this research question reveals that the market share of potential collaborators is higher than that of non-collaborators. Active collaborators command less than half of the market, because not all potential RJVs are realized. Such a distinction between active and potential collaborators is possible with the use of a simulation model.

The second research question was about the effect of competition on the market share of collaborators. Competition increases active collaborators' market share. Working on pooled R&D budgets and exploiting knowledge complementarities creates economies of scale and enable collaborators to succeed in huge R&D projects that no firm can undertake alone in a highly competitive environment. As opposed to active collaborators, potential collaborators are found to lose their market share as competition intensifies. A possible explanation is the negative effect of the resemblance of the product portfolios of the firms in a RJV, which gets even worse with sharpening competition. These opposite results stem from the fact that competition which is driven by the number of new entries every period has a positive effect on the ratio of active to potential collaborator firms by increasing the likelihood of participating in a RJV. The simulation model keeps track of collaboration ratio which explains why potential collaborators can lose their market share whereas active collaborators increase theirs as competition intensifies.

Lastly, technology complementarity boosts the market share of active collaborators motivated by knowledge sharing. The level of knowledge complementarity is a function of the overall heterogeneity in the knowledge pool of firms and there is an optimum level for this heterogeneity beyond which further increases do not bring about any increases in the R&D productivity of alliances. This result stems from the fact that what determines the success of knowledge complementarities is the possibility that two firms at optimum distance from each other in the technique space form an alliance and this possibility is conditioned by the level of knowledge heterogeneity in the firm population. Knowledge heterogeneity has a very similar effect on potential collaborators and the simulation results showed us that collaboration ratio within potential collaborators helps to explain the market share of active collaborators specifically when knowledge heterogeneity is moderate or high.

The simulation analysis in this study enabled us to use two alternative methods to measure market share of collaborator firms. The outcomes of the simulation tests are driven by the chosen method. A clear inference based on these outcomes is that the research results of the empirical studies on RJVs should be interpreted with some caution in regard to the preferred method of defining collaborator firms.

In this paper, firms are endowed with an R&D strategy when they enter the market which they are not allowed to change. A possible extension would be the endogenisation of these strategies by letting firms freely choose and possibly change them according to varying market and technological conditions (e.g. ceasing to go into R&D partnerships once market leadership is gained). However, one should keep in mind that such a realistic move will increase the complexity of the model making the interpretation of the study results even harder. One other avenue for improvement is that the one-dimensional technology space of the model can be substituted with a multi-dimensional one. This will have implications for knowledge complementarities and hence for R&D collaborations.

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