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Research joint ventures in an R&D driven market with evolving consumer preferences: An evolutionary multi-agent based modelling approach

Salih Çevikarslan

RESEARCH JOINT VENTURES IN AN R&D DRIVEN MARKET WITH EVOLVING CONSUMER PREFERENCES:

AN EVOLUTIONARY MULTI-AGENT BASED MODELLING APPROACH

Salih Çevikarslan[a]

UNU-MERIT and Maastricht University

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 will firstly be used to simulate the evolution of an R&D driven market composed of profit-driven firms and boundedly rational consumers. Next, frequently discussed research questions in the relevant empirical literature will be explored. This modelling 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 a significant effect on research results.

1. Introduction

Firms heavily depend on improved products to survive in the competitive markets. A continuous introduction of these new products necessitates both specialised and more types of knowledge, which is almost always beyond the limits of the accumulated knowledge within the boundaries of a single firm. Hence, firms seek outside of the firm 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 with other firms on a reciprocal basis to share knowledge (Morone & 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 integration by means of mergers and acquisitions (Hagedoorn, 2002).

Alongside monetary funding, the contribution of an individual firm to a joint venture involves sharing of human capital, accumulated knowledge embedded in firm-specific factors, and access to information and activities within its own R&D division (which, in most cases, deals with a much wider spectrum of projects than the scope of the joint venture). 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. The factors of production are freely traded in the market but not all of these firm-specific resources are available to other firms (Anbarci et al., 2002). Firms form alliances to share these resources 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 & Meder, 2006).

This study explores three research questions frequently studied in research joint venture (RJV) literature. These questions are related with the effects of being in a RJV, how competition conditions the market share of collaborators and the effect of knowledge heterogeneity on the market share of knowledge sharing collaborators. For this purpose, 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 analyse 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 how one differentiates between collaborators and non-collaborators and how this 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 in a RJV at a given point in time. As will be clear in the following, this discrepancy may have significant consequences for the research results. There are also a few advantages of this evolutionary model over the ones in the relevant literature. To begin with, it is one of the few models studying RJVs with different motives (cost sharing vs. skills 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 organised as follows: Section 2 is a literature review where the research questions are also discussed. This part opens with the incentives to engage in RJVs and continues with the effect of competition on collaborators' market share and knowledge sharing incentives in R&D collaborations. Section 3 details the simulation model. In section 4, the results of the simulation analyses are discussed. Section 5 concludes.

2. Literature Survey and Research Questions

2.1. Incentives to engage in RJVs

R&D is considered by many observers as one of the, until recently, least expected activities that companies would be willing to share with others as it constitutes one of their core competencies. Even so inter-firm collaboration has exploded during the past couple of decades, in parallel to the intensification of international competition, changing the nature of collaboration from peripheral interests to the very core functions of the corporation, and from equity to non-equity forms of collaboration. Importantly, cooperation focusing on the generation, exchange, and/or adaptation of new technologies has risen at very fast rates. These two facts explain why R&D partnering has attracted so much attention during the recent years, both in the academic and in the popular press (Hagedoorn, 2002; Calogirou et al., 2003).

Two major strands of theoretical literature can be distinguished in this field. The industrial organisation literature has extensively examined the incentives and welfare effects of R&D cooperation among competing firms and focused on the role of R&D investments and R&D spillovers. Theoretical contributions in the management literature have stressed that R&D

collaboration aims at minimising transaction costs and exploiting complementary know-how between partner firms (Belderbos et al., 2004).

Cooperative R&D as an arrangement among a group of firms to share the costs and results of an R&D project also helps to correct market failures which prevent firms from conducting the socially optimum level of R&D. Firms refraining from investing in R&D because of the threat of free-riding on the end results are more motivated to innovate if they can find a partner with whom to share risks and costs. RJVs can increase the efficiency of the R&D process through economies of scale, elimination of duplication of effort, dissemination of knowledge, and utilisation of synergies among firms. RJVs also allow firms to undertake costly R&D projects that none would undertake alone (Sinha & Cusumano, 1991). Ahuja (2000) asserted that each single partner can potentially obtain a greater amount of knowledge than would be the case from a comparable research investment made individually (Arvanitis, 2012). Cooperative R&D can be executed in many forms, including R&D contracts, R&D consortia, and RJVs (Sakakibara, 1997).

According to Sakakibara (1997), in the economic literature, firms' motives for participating in cooperative R&D can be divided into two major classes: reasons related to R&D, and reasons unrelated to R&D. The two major R&D-related reasons are enhancing R&D productivity through cooperation on R&D inputs and changing the appropriability conditions of R&D outputs (Katz, 1995; Geroski, 1993). Reasons unrelated to R&D include improved market access through partners and the collection of government subsidies. An extensive survey of incentives, strategies, and outcomes of RJVs by Caloghirou and Vonortas (2000) revealed the following major objectives of firms to join such RJVs:

* Establishment of new relationships
* Access to complementary resources and skills
* Technological learning
* Keeping up with major technological developments

With all their benefits, partnerships have the negative potential to block competition and create various kinds of static and dynamic monopolies in existing and future markets, respectively (Hagedoorn et al., 2000). The threat of anti-competitive behaviour increases significantly when repeated R&D collaboration occurs between firms that also meet in many product markets (Vonortas, 2000). White (1985) suggested that RJVs could reduce the probability of success of R&D by reducing the number of research paths explored toward a solution. RJVs can also slow down the rate of R&D (Katz, 1986) and delay the realisation of an innovation (Ordover & Willig, 1985).

2.2. The effect of being in a RJV on market share

Sarkar et al. (2001) suggested that the propensity to R&D cooperation ('alliance proactiveness') will lead to higher levels of economic performance in terms of sale growth, market share and product development and that alliances between partners of unequal size mostly provide larger firms access to the tacit knowledge of small firms, which in turn benefit from the financial and marketing resources of the larger ones (Arvanitis, 2012). Belderbos et al. (2004) found that competitor cooperation positively affects growth in sales per employee of products and services new to the market and using a combination of objective and subjective measures, Link and Bauer (1989) have shown a positive correlation between cooperative R&D conducted by a firm, the firm's market share, and the productivity of the firm's in-house R&D. Overall, previous empirical work appears to suggest a positive impact of R&D cooperation on firm performance (Belderbos et al., 2006). Hence our first research question is whether collaborators command a higher market share than non-collaborators.

2.3. The effect of competitiveness on RJV

Firms' proactiveness in R&D collaboration is dependent on the level of market competition. If the level of competition is low, they have less incentive to collaborate, since potential gains may be offset by the costs and risks involved. Hence, they rely on their internal resources in their R&D activities. At a high level of competition, R&D collaboration incentives are impeded by the environmental complexity as there is little to be gained from collaboration. Firms facing moderate levels of competition are more inclined to cooperate than firms facing low competition as they have more to gain from collaboration and they are more attractive partners than firms working in a highly competitive environment. Thus, markets with moderate competition may be the ones where collaboration is most likely. That is why some empirical studies predict an inverted U-shaped relationship for the impact of competitive intensity on the likelihood of forming an R&D alliance (Ang, 2008; Wu, 2012; Wu & Pangarkar, 2010). Therefore our next question is what kind of a relationship there is between competition level and the market share of collaborators.

2.4. Skills Sharing

According to Hamel (1991), firms use alliances as an opportunity to internalise the skills or competencies of its partner to create next-generation competencies. Such learning-based arguments imply that a key objective of cooperative R&D is complementary knowledge or skill-sharing among participants (Miotti & Scahwald, 2003). Complementary knowledge here is defined as knowledge that, in combination, yields better R&D results by increasing innovative productivity (Teece, 1992). Kodama (1992) asserted that 'technology fusion' or the combining of existing technologies into hybrid technologies becomes increasingly important for innovation. Cooperative R&D is a way to internalise and combine complementary resources and knowledge

(Sakakibara, 1997). Analysing over 7000 co-operative agreements worldwide, Hagedoorn and Schakenraad (1990) reported that complementarity is one of the primary motives for the formation of joint ventures and research corporations in information technologies, biotechnology, and new materials.

The resource-based view suggests that the degree of heterogeneity in participating firms' capabilities is an important determinant of the success of cooperative R&D. Capability heterogeneity is defined here as the breadth or diversity of technological capabilities of firms. Today's highly sophisticated innovations often depend upon work across several areas of science and technology (Hagedoorn, 1993). Few firms have the breadth of knowledge required for such undertakings (Randor, 1991), and so a new combination of core competencies is necessary to build core competencies (Hagedoorn, 1995; Tyler & Steensma, 1995 as cited in Sakakibara, 1997, p. 147). Partnerships in which firms have high compatibility in organisational processes and partner-specific absorptive capacity allowing for effective transfer of know-how tend to outperform partnerships in which overlapping knowledge is narrow (Dyer & Singh, 1998; Mora-Valentin et al., 2004). Anbarci et al. (2002) also stressed the importance of complementarity between cooperating firms' R&D processes and R&D inputs in RJVs (Belderbos et al., 2006).

There are two conditions that have to be fulfilled for these RJVs to succeed: first, the partners require some level of technological overlap to facilitate knowhow exchange. Second, their knowledge bases have to be different - otherwise nothing can be learnt (Mowery et al., 1998). Hence, optimal learning entails a trade-off between the advantage of increased cognitive distance for establishing new linkages and for the emergence of innovations and the disadvantage of less mutual understanding (Cohen & Levinthal, 1990). If the value of learning is the mathematical product of novelty value and understandability, it has an inverse U-shaped relation with cognitive distance, with an optimum level that yields maximal value of learning (Wuyts et al., 2005). Because firms motivated by knowledge sharing pick their partners according to this criterion, our last research question will be whether higher capability heterogeneity among firms will mean higher market share of collaborators motivated by knowledge sharing.

As a final point, technological overlap among alliance partners may increase over the course of collaboration, as a result of organisational learning and technology transfer within the venture (Mowery et al., 1998). Partner firms start to resemble each other in regard to their product portfolio and R&D routines after having RJVs experiences together. Whether this common history contributes to their prospective joint R&D projects' success and hence to their tendency to work together in the following periods depends on their dynamic cognitive distance.

3. The Model

This is an agent-based model, agents being firms and consumers. The agents follow pre-specified heuristics (e.g. innovation routines, R&D partnering, product purchases) and react to competitors and environmental conditions (e.g. pricing). The interactions between these agents at the micro level determine macro outcomes. The model will show how these outcomes are conditioned by the parameters of interest.

The model addresses the supply and demand side of the market simultaneously with the coevolution of heterogeneous consumer preferences, heterogeneous firm knowledge bases and technology levels at the micro level. In line with the evolutionary modelling tradition, we have a search algorithm (innovation and imitation of products by firms), a selection algorithm (revealed consumer preferences), and a population of objects in which variation is expressed and on which selection operates: namely, firms (Windrum, 2007).

The model will show how firms and consumers interact in the market environment and how this interaction leads to technological progress. Firms compete on price and quality of their products in an oligopolistic market and they engage in innovation or imitation activities to increase their quality. Firms are endowed with their fixed innovation strategies. Consumers with heterogeneous preferences and constrained by their computational limits act to maximise their utility with their product choices shifting their preferences towards higher quality goods as their preferences coevolve with technology production by firms. Firms reaching higher quality levels earlier than their competitors gain a competitive edge in the market. Demand is differentiated and new products create new sub-markets loosely competing with the existing ones.

Firms pick a price for their goods and put them on the market for consumers' purchase. To make their products visible to potential buyers they make some marketing expenses. Consumers sample a few products and compare them with their previous experiences to buy one that fits best with their preferences. A part of the revenue raised with product sales finances firms' R&D activities. In accordance with its strategy, a firm makes an innovation or imitation to add a new product to its portfolio either in an R&D collaboration or on its own. Depending upon their competitive performances goods and incumbent firms leave the market leaving their places to new generation of goods and newcomer firms, respectively.

3.1. Technology Space

Each product and technology (knowledge) embodied by this product is labelled by an integer number. The words "product", "quality" and "technology" will be used interchangeably in the following. A bigger number corresponds to a higher quality product and a better technology. The units digit of this number shows the version of the product while the rest of the number shows the class the product belongs to. As an example, the number 23 refers to the third version of the

second class of products. Hence, each class consists of ten versions. A class is significantly different from any other in terms of its technological level whereas there are only incremental differences between versions in this regard. Products high on the quality ladder (Grossman & Helpman, 1991a; 1991b) -products belonging to higher classes or higher versions within a given class- are intrinsically better than the lower ones. The distance between the highest version in a given class and lowest version in a consecutive higher class is a parameter of the model and there are no defined products in between. Hence the technology space resembles an infinite series of quality ladders on top of each other, each ladder stands for a technology class and each step for a version, and a move from one class to the next requires a jump between the ladders which is only possible with a radical innovation.

3.2. Demand and Supply Structure

Firms compete on quality and price of their differentiated products in an oligopolistic market. There are no production quantity constraints on the firms and all demand is satisfied in every period, there is no stock accumulation or unsatisfied demand. The production cost of a product is linearly related with its quality. Price is initialised as a mark-up over cost and this is the minimum price allowed, which means that sales of a product always bring positive profits and *ceteris paribus* higher quality products mean higher profits. Pricing strategy is a dynamic mark-up heuristic through which firms decide price of each good every period as a function of quality of and profits from that product. Specifically, the proportional change in price is a linear function of the proportional change in the profits on that product in the last two periods. The responsiveness of price to a change in profit is smoothed by a parameter s. A product with no sales in the last but one period is priced at its initial price.

$$C(n) = mq(n) \tag{3.1}$$
$$p(n) = (1 + \mu)C(n) \tag{3.2}$$
$$p(n, t+1) = p(t) + s(p(t)((\pi(n,t) - \pi(n,t-1)) / \pi(n,t-1))) \tag{3.3}$$

where $C(n)$: cost of product n

     m : cost multiplier

     $q(n)$: quality of product n

     $p_i(n)$: initial price of product n

     μ : mark-up rate

     $p(n,t)$: price of product n at time t

     s : smoothing parameter

     $\pi(n,t)$: profit on product n at time t

If a product's average market share over a specific number of periods is below a threshold level, it is deleted from the market. A firm with no products to sell goes bankrupt. Every period a constant number of firms enter the market as an exact copy of an already existing firm, except for its innovation strategy that is randomly determined. The firms that are copied by the new entrants are selected among the ones with a market share below a certain level. This seems a reasonable approximation of reality because in practice most firms start small (de Wit, 2005; Dunne et al., 1988).

Consumers have what we call a *memory set* which consists of a number of goods selected among all the products the consumer considered to buy in the previous periods. This selection is based on the utility level the product would bring to the consumer in case of a purchase. At every period, the consumer checks whether the products in the memory set are still provided by the market. If any of them is removed from the market, it is replaced by a new randomly selected product. Again at every period, consumers randomly sample a number of products from randomly selected firms. The probability that a product is selected is proportional to the marketing expenses by the firm on that product.

A constant share of the last period's revenue, which is equal for each firm, is spent on marketing activities to make goods visible to the consumers and this marketing budget is shared among products according to their quality level. Specifically, the visibility of a good is the average of the marketing expenses on that good for the last five periods. Price is initialised as a mark-up over cost, which is a linear function of quality, and this is the minimum price allowed. Hence higher quality products bring higher profits and this is why goods consume a share of marketing budget in proportion to their quality.

The newly selected product is compared with the current minimum utility promising product in the memory set and replaces this if it corresponds to a higher utility level for the consumer. Out of this dynamically structured memory set, the good that brings the highest utility is chosen to buy in every period. There are no income constraints faced by the consumers. This product selection heuristic is a decent representation of the basic evolutionary processes of reproduction (keeping the highest utility promising products from the previous periods), selection (choosing among products to maximise utility), and variation (a continuous and random selection of new products). The existence of a memory set and the peculiar way products become visible to the consumers enable us to model brand loyalty and advertising effects, respectively (Malerba et al., 1999).

Utility is a positive function of the quality and a negative function of the price, and the distance between product's profile and idiosyncratic ideal good specific to each customer profile (Marengo & Valente, 2010). At the outset, the consumers position themselves within the available technology space into consumer profiles or let us say, submarkets. The number of submarkets is constant and each submarket corresponds to a point in the technology space

between current minimum and maximum quality levels. The total number of consumers is uniformly distributed into these submarkets and this relative positioning somewhere between the minimum and maximum available technology level in the market is constant through the simulation run. Figure 1 exemplifies this distribution. This formulation allows one to model heterogeneity in consumer preferences; consumers consist of early adopters with a strong preference for high-tech goods, low-price lovers who are content with low quality goods and the ones seeking a balance between price and quality. As technology develops (the level of minimum and maximum available technology improves), preferences shift towards higher quality products increasing the quality of the ideal type good for each consumer. The fact that homogeneous consumers are populating submarkets can be interpreted either as there are as many consumers as the number of submarkets and each of these consumers is making a group buying every period or the submarkets consist of a number of homogenous consumers buying the very same product.
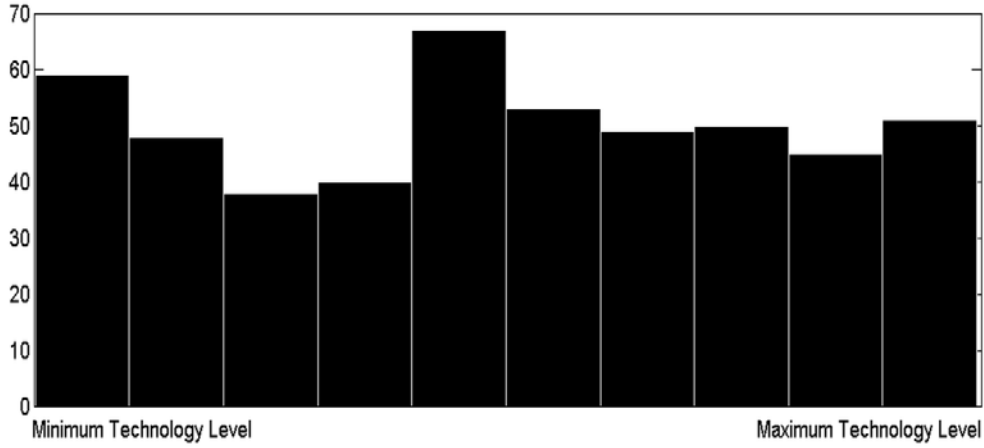

Figure 1. A histogram showing the uniform distribution of the customers' ideal product profiles within the available technology space

$$U(n,k,t) = [r\{q(n) - \mod(q(n),10)\} + \mod(q(n),10)] - p(n,t) - |(q(n) - q_i(k,t)| \qquad (3.4)$$

$$q_i(k,t) = q_{min}(t) + u(k)(q_{max}(t) - q_{min}(t)) \qquad (3.5)$$

where $U(n,k,t)$: utility of good n for customer k at time t

$\quad r$: radical innovation constant

$\quad \mod(q(n),10)$: $q(n)$ mod 10

$\quad q_i(k,t)$: ideal good profile for consumer k at time t

$\quad q_{min}(t)$: minimum quality level at time t

$\quad q_{max}(t)$: maximum quality level at time t

$\quad u(k)$: a random pick from a uniform distribution between 0 and 1 for each customer at the outset

The first part of the utility function in the square brackets gives the positive utility derived from the quality of the product. This part is separated into two dimensions: the class that the product belongs to, as given by the part in the curly brackets, and the version of the product within that class which is represented by the unit digit of the product quality number. This separation between class and version of a product in utility terms requires us to use modular operation. Modular operation finds the remainder of division of one number by another. To give an example, A mod B can be thought of as the remainder, on division of A by B. The divisor (B in our example) in our case is 10, because there are exactly 10 versions within each class. A distinction is made between the class and version of a product since consumers attach different levels of values to these dimensions.

Consumers care more about the class of a product rather than its version within a given class. This distinction is operationalised by the parameter r. The parameter r is defined as the radical innovation constant and determines, ceteris paribus, by how much two consecutive versions in different classes differ from each other compared to two consecutive versions in the same class in utility terms. To put it another way, r indicates by how much the first version in a class is evaluated better than the last version in a lower class in comparison to one version is evaluated better than a one degree lower version in the same class holding all else constant. The higher the r the higher is the possibility that higher class products will be preferred over lower class products. $r = 1$ presents a special case where there is no more a distinction between the class and the version of a product. Under such a circumstance it will take longer for the inferior products to be eliminated, product range will increase and technological change and hence wealth creation will slow down, since consumers no more put a premium on radical innovations.

The price of a product appears in the utility function with a negative term. The last part of the utility function in the absolute terms gives the negative utility due to consuming a non-ideal product. This form of the utility function allows one to model heterogeneity in consumer tastes with the inclusion of the distance of the candidate product from the ideal one and to model the process whereby products transform from non-invented to invented and from cutting-edge to obsolete in time with a continuous shift of preferences towards higher quality products as explained previously. This process is especially accelerated with an r value higher than 1.

3.3. Innovation and Imitation

Innovation is defined as the emergence of a new product. The firm chooses a product to invest in from its portfolio and does R&D. The quality level of this product also shows the knowledge base of the firm in that specific project. Innovation size is modelled as a random pick from a Poisson distribution with an arrival rate which is a function of the quality of the product invested in and the R&D budget devoted to that project (Minniti et al., 2013). The arrival rate is a negative function of the quality of the product to invest in: complexity of the product decreases the likelihood of the research success. And there are diminishing returns to R&D; additional

investments increase the arrival rate in a decreasing manner. Hence, a lower level for the complexity of the knowledge base and more R&D investment increases the size of an innovation.

When innovation occurs, the resulting difference (the size of the innovation) is added to the chosen product's technology level. A new product embodying a new technology and a higher technology base emerges. If the newly innovated product is in a higher class, then we have a radical innovation. Otherwise we have an incremental innovation. Depending on the radical innovation constant (r) parameter value, radical innovations may render old technologies in the market obsolete whereas incremental ones do not have such an impact. Hence a radical innovation may disturb the profit stream from the lower-class products which means that a firm can cannibalise its own products. This feature is introduced to the model with the specification of the utility function whereby higher-class products will have a market stealing effect on the lower-class products.

In the case of a radical innovation, the size of the innovative step is large enough to cover the sum of the distances between the knowledge base and cutting edge technology in the respective class and the distance between two consecutive classes where no products are defined. The size of an innovative step is limited to a maximum of one radical innovation at a time. When there is a radical innovation, the newly innovated product will be allowed at most to be the lowest version in the new class and nothing higher. This constraint negates the possibility that the knowledge base achieved in the previous class helps explore the technology space of the new class of products. If the resulting innovation appears to be in the interval between two classes where no products are defined, then the innovation project is assumed to fail.

$$\lambda(n,i,t) = \frac{R(n,i,t)^{\alpha}}{q(n)} \qquad (3.6)$$

$$\delta(n,i,t) \square Pois(\lambda) \qquad (3.7)$$

$$q(n') = q(n) + \delta \qquad (3.8)$$

where $\lambda(n,i,t)$: innovation arrival rate for product n of firm i at time t

$R(n,i,t)$: R&D investment of firm i in product n at time t

α : innovation productivity parameter

δ : innovation size, a random pick from a Poisson distribution with arrival rate λ

$q(n')$: quality level of the innovated product

Imitation is defined as creating an exact copy of another firm's product. Once the product to invest in is chosen within a firm's own portfolio, the firm determines the expected size of the imitative step given its R&D budget and base technology. Then, it searches through the product sets of other firms to find this prospective target product. If this product is not innovated yet or not extant anymore, the firm seeks for a one step lower technology. If needs be, the firm repeats

this search cycle with the next base product. After this search process is over, if no viable imitation projects can be determined, idle R&D budget is transferred to the R&D budget of the next period. The size of the imitative step is modelled with the same function given for innovation projects except for the fact that R&D investment is more productive in imitation than in innovation. If imitation succeeds, –the imitative step is at least as large as the distance between the base product and the target product- the end result of the project can only be the target product itself and nothing else. Even if the imitative step is bigger than the difference in the technology levels, the firm will be assumed to achieve the target quality, but no higher.

$$\lambda(n,i,t) = \frac{R(n,i,t)^{\beta}}{q(n)} \tag{3.9}$$

$$\delta(n,i,t) \square \ Pois(\lambda) \tag{3.10}$$

$$q(n') = q(n) + \delta \tag{3.11}$$

where $\lambda(n,i,t)$: imitation arrival rate for product n of firm i at time t

$\quad R(n,i,t)$: R&D investment of firm i in product n at time t

$\quad \beta$: imitation productivity parameter

$\quad \delta$: imitation size, a random pick from a Poisson distribution with arrival rate λ

$\quad q(n')$: quality level of the imitated product

A firm is either an innovator or imitator from the beginning and stays as such throughout the simulation. Every firm engages in one R&D project at a time and in picking R&D projects, they pursue a technology-push strategy. They select R&D projects starting from the highest technology base they possess to come up with cutting edge technology possible. The financial resources required to imitate a product are lower than to innovate one and the chance of success is higher. However, the profits especially from a new-to-the-market innovation are higher compared to an imitated product for which the market is already satisfied at least to some degree.

3.4. R&D Productivity

This study defines R&D productivity as the efficiency at which R&D budget is exploited for product development projects (parameters α and β in equations 3.6 and 3.9, respectively). For non-collaborators, this efficiency is the same and constant for all firms. For collaborators, it is limited between a maximum and minimum level and its exact value is a function of the difference in techniques between partners. For this model, technique can be interpreted as the way of doing R&D. Each firm is assigned a random value in one-dimensional technique space when it enters the market. There is an inverted U-shape relationship between difference in techniques and R&D productivity of the joint R&D project (Figure 2). This kind of a relationship derives from the effect of knowledge complementarities on research success. If two firms are very similar in the

way they perform R&D, then there is not much to gain from this partnership. There is not much point in tapping into the knowledge base of your partner as it mostly overlaps with yours. If there is a radical difference in their R&D techniques, potential knowledge complementarities are overshadowed by communication problems. The firms are too different to learn from each other. In both cases, R&D productivity can be lower than what it would be if these firms chose not to collaborate. The best of both worlds lie somewhere in between: when firms differ enough so that there is something to learn from each other, but still they are similar enough so that they can share their accumulated knowledge to exploit knowledge complementarities. Therefore R&D productivity reaches its peak at a moderate level of difference in techniques.
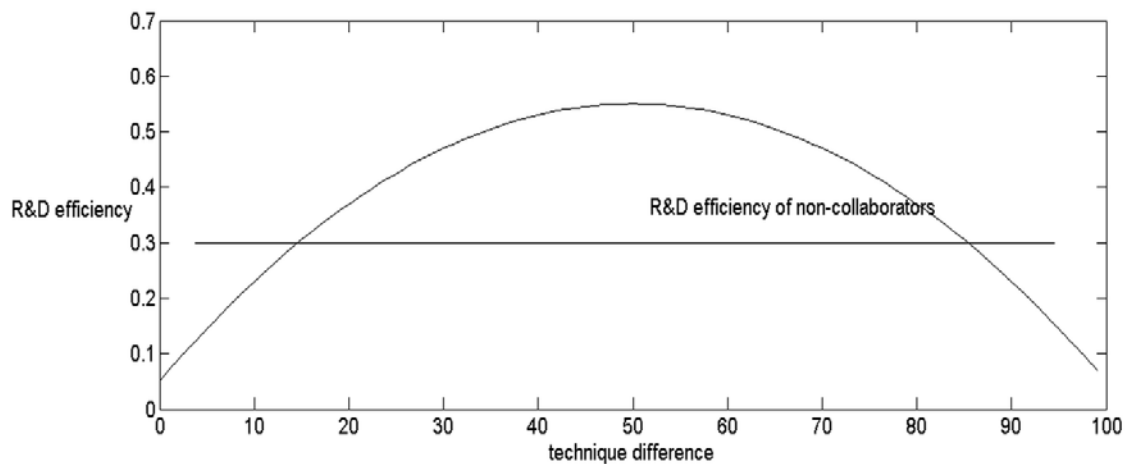

Figure 2. R&D efficiency of a RJV as a function of the difference in techniques between firms

3.5 Partnering

Partnerships are only formed for the sake of technology development projects and whether a firm collaborates or not depends on its strategy. Firms do not change their strategies throughout the simulation. There are collaborator and non-collaborator firms and whereas non-collaborators make R&D in isolation, collaborators always find a partner if they can. Any given collaborator firm partners with only one firm at a time and two firms should have the same strategy to go into a partnership (e.g. knowledge sharing innovators only collaborate with knowledge sharing innovators and cost sharing imitators only collaborate with cost sharing imitators). Two firms should be planning to invest in the same of class of technology to go into a partnership. This way the firms high on the technology ladder are prevented from being exploited by the firms working with comparatively inferior technologies. The RJVs are formed for a single R&D project and dissolved once the project is over.

Collaborators are divided into two groups according to their motivation for partnering and hence the way they choose their partners. Following the stream of evolutionary economists (e.g. Nelson

& Winter 1982, Dosi, Freeman, Nelson, Silverberg, & Soete, 1988) the choice of the cooperation partner is based on the participating firms' assets of routines and resources developing over time (Cantner & Meder, 2006). The firms motivated with knowledge sharing partner with firms which are at optimum distance from them in technique space in order to maximise their R&D productivity. The firms motivated by cost sharing partner with firms with the largest possible R&D budget. Because technique and R&D budget is a symmetric measure (they do not differ according to the perspectives of different firms), a partnership carries the same weight for both sides and hence, all partnership offers are accepted. For knowledge motivated firms, in technique space, if firm A is at optimum distance from firm B so is firm B from firm A. In a parallel vein among cost motivated collaborators, firm A offers partnership to firm B which has the highest R&D budget after firm A and this offer is accepted, because firm B cannot get a better offer from another firm.

As a final point, firms move toward each other in the one-dimensional technique space when they engage in a RJV. Working on the same product development project make firms resemble each other in the way they perform R&D. Depending on their relative positions in the technique space before the project, this step towards each other either increases or decreases the possibility that two knowledge sharing firms collaborate in the following rounds. After several R&D projects together, it will be highly unlikely for these two firms to go into a partnership, since there will not be much left to learn from each other. This tendency will drive knowledge sharing incumbent firms to partner with new entrants in the long term.

3.5. The Pseudo-Code of the Model

At the initialisation period, market is populated with N firms each endowed with a random R&D strategy, 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 their each product as a function of profits from that product in the previous periods.
2. Firms make marketing expenses for their 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.

4. Simulation Analysis

4.1. Model Dynamics

In the following we will present the results of the simulation analysis[2]. The data for the analysis is produced as an average over 100 simulation runs of 1000 steps using the base model configuration. The only thing that changes from one simulation to the other is the seed value which is a number used to initialise the pseudorandom generation process. This seed value governs all the stochastic processes within the model and two simulations with the same seed value always give the very same results. We start with introducing the evolution of the main variables of interest to show how R&D activities of firms and heterogeneous consumer preferences interact in structuring the evolution of an industry.

Figure 3 reports inverse Herfindahl index[3]. The inverse Herfindahl index is the number of firms with equal market share that would generate the same concentration as that measured in the actual market, consequently measuring the dispersion (or inverse of concentration) of the market (Marengo & Valente, 2010). Figure 3 signifies a severe shake-out of firms from the beginning of the simulation run until the figure reaches its lowest value when the market concentration is at its maximum. This is followed by dispersion where a higher number of firms share the market creating a more competitive environment and stabilisation for the following periods. The model is initialised with a population of firms and those which cannot successfully serve to heterogeneous consumer needs are eliminated from the market in the early periods stabilising the concentration rate for the following terms.
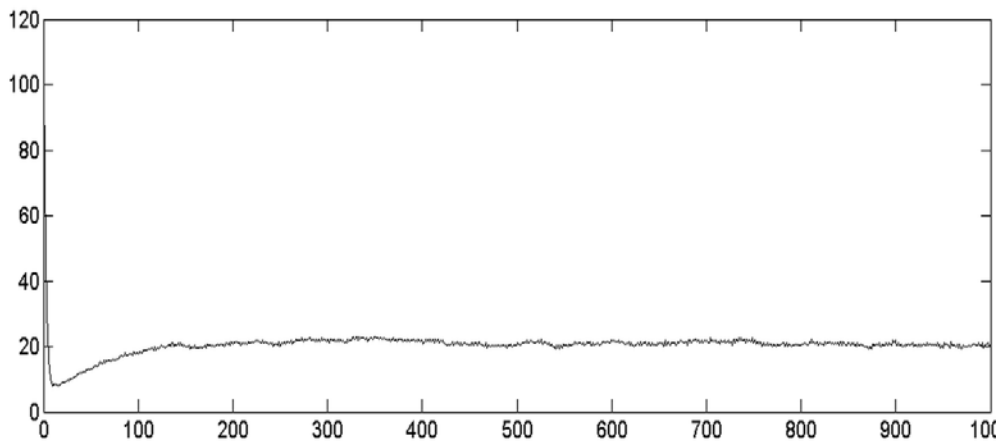

Figure 3. Inverse Herfindahl Index

[2]The model was implemented on the Laboratory for Simulation Development platform (Valente, 2008). Software and documentation for the platform are available at www.labsimdev.org. The code and configuration file of the model is available from the author upon request.

[3] The formal definition of the inverse Herfindahl index is $1/\sum_{i=1}^{n} s_i^2$ where s_i^2 is the squared market share of firms.

Figure 4 traces the time-path of the market shares of the groups of firms following one of six different strategies: non-collaborator innovators, non-collaborator imitators, knowledge-sharing collaborator innovators, knowledge-sharing collaborator imitators, cost-sharing collaborator innovators, and cost-sharing collaborator imitators. The figure shows that heterogeneity in firms' innovation strategies is sustainable; every strategy enjoys a positive market share throughout the simulation run. Figure 4 also signifies a shake-out of the market shares in the initial periods followed by a dispersion and stabilisation for the following terms.
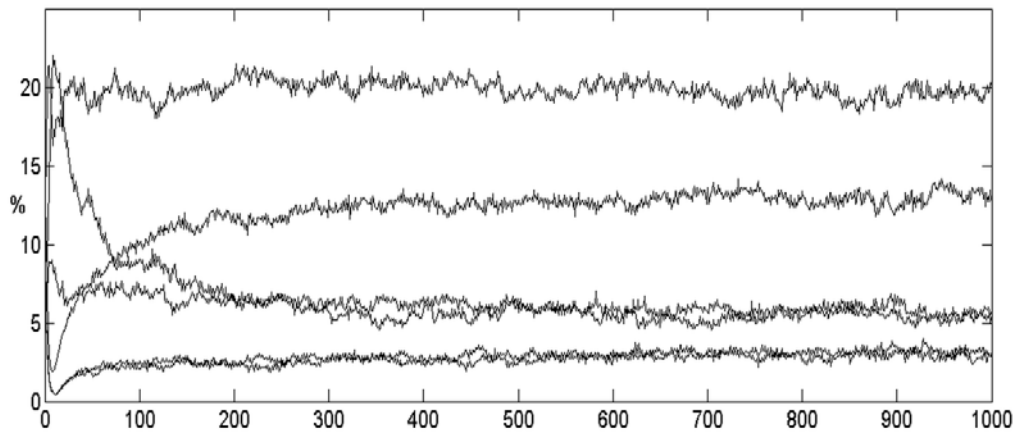

Figure 4. Market shares (%) of firm groups following different R&D strategies

Figure 5 allows us to observe the maximum (upper series) and the minimum (lower series) level of product qualities available in the market. Whereas the maximum quality level is mainly determined by the R&D activities of the firms and the minimum level mainly by the competitive forces and heterogeneous consumer tastes, the interaction between demand and supply dynamics affects these levels both. The continuous introduction of new products by innovation raises the maximum quality and renders low quality products obsolete by shifting consumer preferences towards high-tech products. Technological change is the engine of economic growth in this model. If for some reason technology creation comes to a halt (e.g. imitators conquer innovators dominating the whole market and leaving innovators with no financial resources to innovate), the economic growth also stagnates. Therefore both consumers and imitator firms depend upon innovator firms to prosper.

Going into an R&D partnership requires firms to have the same R&D strategy and to invest in similar technologies. Even if these criteria are met, a possible partner might already be in an R&D collaboration. This means at a given time, only some of the potential collaborator firms are actually in a RJV. Figure 6 below shows this ratio of the number of active collaborators to potential collaborators. The ratio is very high in the initial periods when the firms are quite homogeneous in their product portfolios. As product range increases together with technological progress, it swiftly decreases and then levels off for the following periods. There are two alternative explanations for the fact that not all prospective collaborators are in collaboration at
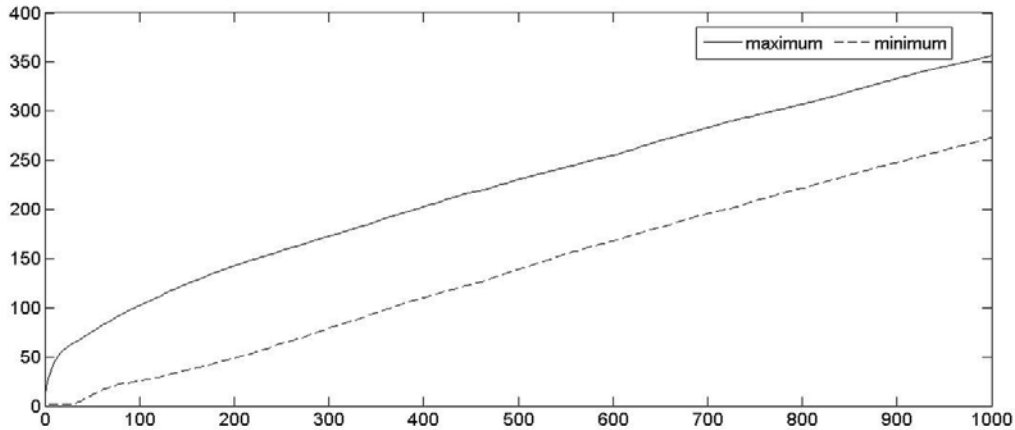
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Figure 5. Maximum and minimum quality levels available

every period. Either some of them (roughly 65% for the second half of the simulation run) are continuously collaborating whereas others are generally unable to find a partner or most of the firms are in collaboration during some part of their life and in isolation for the rest. A closer examination of the simulation results shows that the latter is the case. An average potential collaborator spends some of its time in R&D collaborations and some for individual projects. Then the question arises as to when a firm should be regarded as a collaborator especially in collecting macro data. At a given period should a prospective collaborator's market share add to the total market share of collaborators irrespective of whether it is actually in a partnership or not at that specific period or should only active collaborators' market share count? This paper shows that the answer to this question determines the outcomes of our research questions.
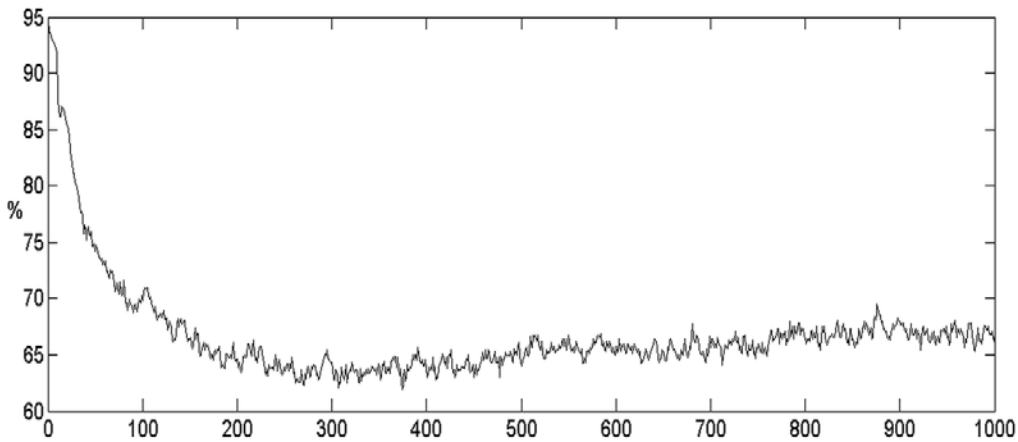

Figure 6. The ratio (%) of active collaborators to potential collaborators

An interesting follow-up question is how this ratio of active to potential collaborators is affected by a behavioural rule (R&D intensity) and a structural market characteristic (market size). These effects can be observed in Figure 7 for R&D intensity and in Figure 8 for market size. The higher the level of R&D intensity and the bigger the market size, the lower this ratio. The explanation for this lies in the evolution of product ranges of firms. A higher R&D intensity or a bigger

18

market allows a firm to have an increased product range, which makes it less likely for a potential R&D collaborator to find a partner planning to invest in a similar product.
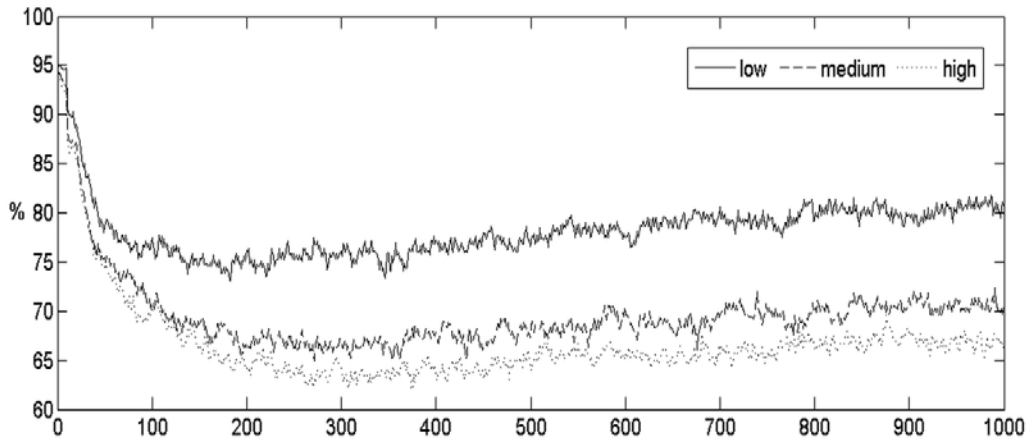

Figure 7. The ratio (%) of active collaborators to potential collaborators when R&D intensity is low, medium and high
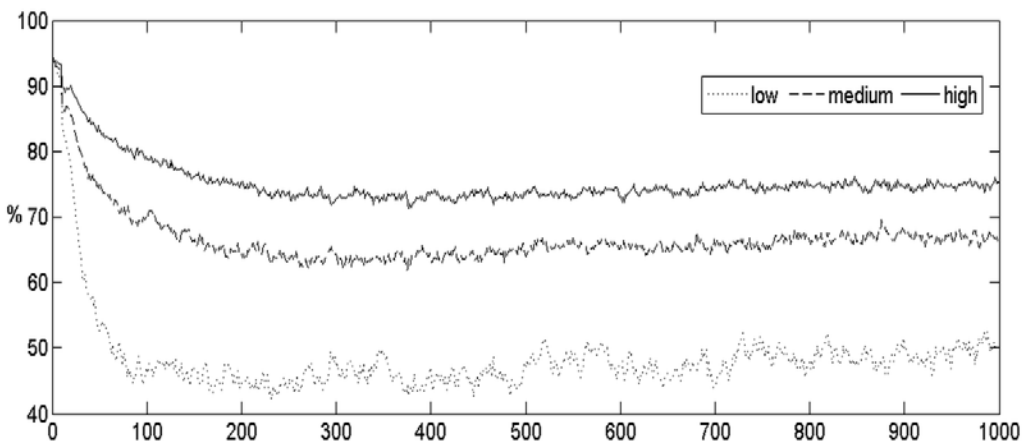

Figure 8. The ratio (%) of active collaborators to potential collaborators when market size is small, medium and high

4.2. Simulation Experiments

This subsection includes the results of a series of simple simulation experiments designed to answer our research questions. 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. At this point the reader should be reminded that there are 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. The distribution of the end of simulation value of the market share of collaborator firms is drawn as a box plot in Figure 9 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[4]. The Lilliefors test also confirms this result. 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 exemplifies how the way one differentiates between collaborators and non-collaborators produces opposite results to the very same research question.
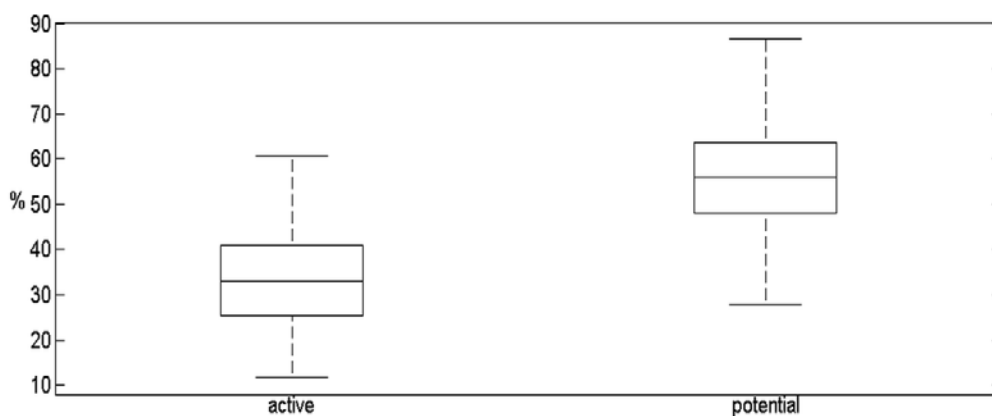

Figure 9. The market share (%) of active and potential collaborator firms

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Our second question was what kind of a relationship there is between competition level and market share of collaborators. Figure 10 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 when the level of competition is low, the sample does not follow a normal distribution. This result is confirmed by the Lilliefors test. Therefore, Wilcoxon rank sum test will be used to test the null hypothesis that the samples have equal medians. The hypothesis test results complement our graphical analysis; the median value when competition is high is statistically significantly higher than the median value when it is medium, which in turn is significantly higher than the median value when it is low. Therefore our hypothesis is rejected.
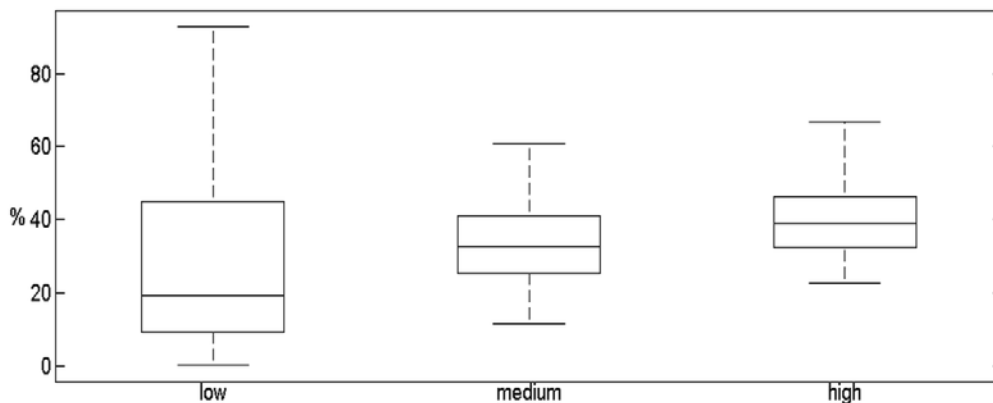

Figure 10. The market share (%) of active collaborator firms when the level of competition is low, medium and high

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 11 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 emphasised 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 tests show that 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 test to investigate the null hypothesis that the samples have equal means. The test results conclude that the median value when competition is high is statistically significantly higher than the median value when competition is moderate, which in turn is again significantly higher than the median value when competition is low. 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 of the simulation data. 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 12 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.
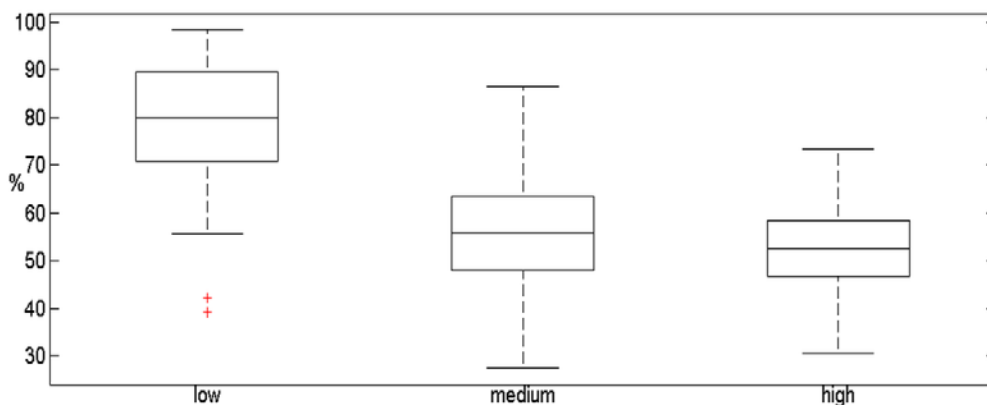

Figure 11. The market share (%) of potential collaborator firms when the level of competition is low, medium and high
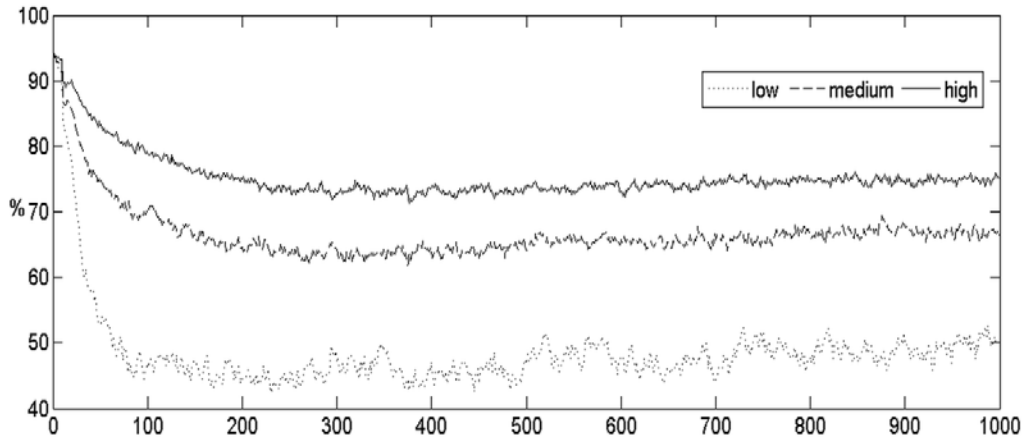
Figure 12. Collaboration ratio (%) when competition is low, medium and high

In the literature survey it was 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 13 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 0.5%, 25%, and 22%, 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 due to the fact that 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 and Lilliefors tests, it is concluded that the samples do not come from normal distributions. Hence, Wilcoxon rank sum test is performed to see whether there is a statistically significant difference between the median values of the samples. 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 perfectly support the graphical analysis.
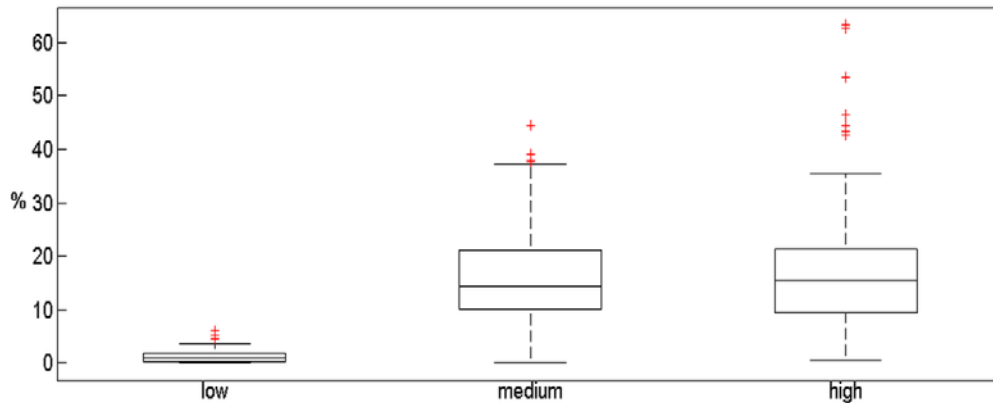

Figure 13. The market share (%) of knowledge-sharing active collaborators when knowledge heterogeneity is low, medium or high

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 14. It is very similar to Figure 13 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 and Lilliefors tests show that the samples do not come from normal distributions. In order to test whether there is a statistically significant difference between the median values of the samples, Wilcoxon rank sum test is used. The results are exactly the same as for active collaborators. 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. 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 15 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. Apparently the reason for the low market share of knowledge-sharing active collaborators in this case is the low market share of potential collaborators.
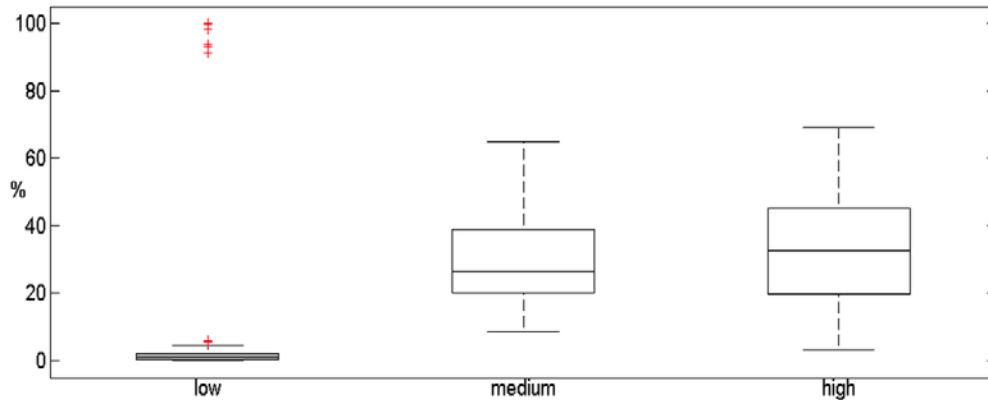
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Figure 14. The market share (%) of knowledge-sharing potential collaborators when knowledge complementarity is low, medium or high
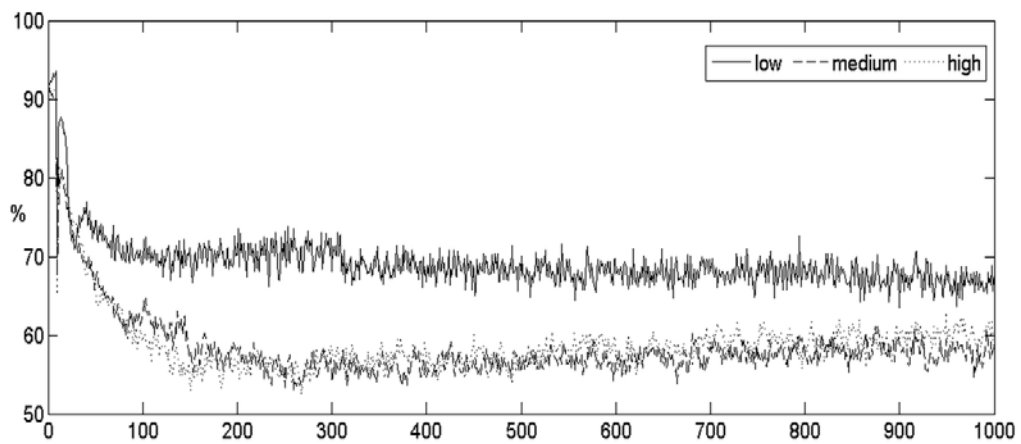

Figure 15. Collaboration ratio (%) within knowledge-sharing potential collaborators when knowledge complementarity is low, medium or high

5. 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 maximise 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 realised. 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. This 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 collaboration ratio within potential collaborators helps to explain the market share of active collaborators specifically when knowledge heterogeneity is moderate or high.

The outcomes of the simulation tests in this study are driven by the chosen method of measuring market share of collaborator firms. 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 chosen 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. It also remains to see what happens when a structural market characteristic (e.g. market size) or a behavioural rule (e.g. R&D intensity, utility function) is changed.

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