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Absorptive Capacity and Innovation: When Is It Better to Cooperate?*

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Abstract

Cooperation can benefit and hurt firms at the same time. An important question then is: when is it better to cooperate. And how can an appropriate partner be selected? In this paper we present a model of inter-firm cooperation driven by cognitive distance, appropriability conditions and external knowledge. Absorptive capacity of firms develops as an outcome of the interaction between absorptive R&D and cognitive distance from voluntary and involuntary knowledge spillovers. Thus, we offer a revision of the original model by Cohen and Levinthal (1989) accounting for recent empirical findings and explicitly modeling absorptive capacity within the framework of interactive learning. We apply that to the analysis of firms' cooperation and R&D investment preferences. While the focus of this paper is limited to a static scenario, where the cognitive distance between cooperating firms is fixed and given exogenously, in Savin and Egbetokun (2012) we address the dynamic approach and provide more extensive simulation results.

Keywords: *inter-firm cooperation; absorptive capacity; cognitive distance; innovation; knowledge spillovers*

JEL Classification: *C63, D83, L14, O32, O33*

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1 Introduction

This paper presents a new theoretical model of absorptive capacity and cooperation between firms. The aim is not to completely capture the motivations for cooperation; rather, we focus on a very specific effect, that is, knowledge sharing or what De Bondt (1996) termed the "voluntary exchange of useful technological information". In this sense our model shares the features of Cowan's et al (2007) model of bilateral collaboration where firms form alliances purely based on the production of shared knowledge.

Inter-firm cooperation for learning and innovation has become more common in recent years, mainly due to rapid technological progress and changes in the business environment. Quickly advancing technological knowledge and rising costs of R&D make it virtually impossible for any firm to maintain in-house all the capabilities and knowledge required for production. Moreover, increasing specialisation creates a situation where firms occupy relatively narrow positions in the knowledge space. Consequently, firms often need knowledge[1] that lies outside their core competence. The formation of alliances with other organisations has proven to be an effective way to access external knowledge to complement endogenous capabilities (Powell and Grodal, 2005; de Man and Duysters, 2005; Brusoni et al, 2001; Bamford and Ernst, 2002; Powell, 1998).

For such alliances to have the desired effects, firms require absorptive capacity to understand and apply knowledge generated elsewhere. This capacity is developed by investing in R&D (Cohen and Levinthal, 1989, henceforth CL).[2] Moreover, the effectiveness of alliances is known to have an inverted 'U'-shaped relation with cognitive distance. In alliance formation, therefore, firms need to balance between their technological heterogeneity and overlap with potential partners (Nooteboom, 1999). This creates a proximity trade-off and has been a major focus in the recent literature.[3]

However, other issues are also important. Reciprocal terms of cooperation require a firm to share some of its knowledge with the partner in order to gain access to the latter's knowledge base (Fehr and Gächter, 2000). This is like a 'two-edged sword'; if the partner can learn faster and is more capable to innovate, the firm then runs the risk of making its partner better at its own expense. For this reason, voluntary spillovers or appropriability conditions between cooperation partners become a very critical factor to consider in cooperation. For the same reason, a firm will take the R&D efforts of its potential partner seriously since that is the main source of absorptive capacity. When these are combined with the challenge of cognitive distance, an important practical question arises: when is it better for a firm to cooperate?

In this paper, we approach the question from a theoretical perspective by looking at the contribution of absorptive capacity (driven by cognitive distance, appropriability conditions and external knowledge) to firms' R&D profit, and examine where a cooperating

[1] Henceforth, knowledge in this sense includes technologies that firms use in innovation. Innovation refers to a technically new product which develops as an outcome of R&D (see Oslo manual, Organisation for Economic Cooperation and Development (OECD), 2005). Consequently, by R&D profit we imply profit due to innovation.

[2] Although recent studies have argued that absorptive capacity, being a multidimensional concept, is not fully proxied by R&D or staff quality alone (Flatten et al, 2011; Zahra and George, 2002), we assume that a significant portion of it is embodied in R&D performance. Therefore, our conceptualisation of absorptive capacity in this paper derives mainly from a firm's R&D investments.

[3] Some studies (e.g., Cantner and Meder, 2007; Mowery et al, 1996) have also shown that cognitive proximity reduces over time. This affects the learning and innovation potential of an alliance and reduces the likelihood that the same partners will cooperate in the next period. This dynamic is important and we address it in a companion paper (Savin and Egbetokun, 2012).

firm will outperform a non-cooperating one. To do this, we develop a model of inter-firm cooperation in which partners increase their knowledge stock by sharing complementary knowledge. The amount of external knowledge absorbed depends on absorptive capacity, and the new knowledge affects firm performance through innovation-driven profit. Two things set our model apart. First, a firm develops absorptive capacity not as a side-effect of total R&D but by devoting a share of its total R&D budget explicitly to it. This creates an investment trade-off. Second, accounting for cognitive distance allows us to distinguish voluntary spillovers within an alliance from other forms of external knowledge. With these elements, we are able to modify the original absorptive capacity model of CL for the context of inter-firm alliances. We use that to study how cooperation affects firm performance in terms of profit.

This study contributes to understanding cooperation and R&D investment preferences of companies and, therefore, has important theoretical and practical applications. The theoretical predictions of our model are more relevant in the context of interactive learning, and our comparative results offer some practical insight on alliance formation decision-making. However, in this study our focus is limited to a static scenario (where cognitive distance and absorptive capacity of firms are not affected by their past decisions). In the companion paper (Savin and Egbetokun, 2012) we extend our model to analyse the dynamic scenario in order to cover those issues.

2 Literature overview

Technological progress develops along certain trajectories within a given technological paradigm. Each of these trajectories contains some technological opportunities which are either intensive or extensive. In the former case, companies explore opportunities on a particular trajectory by investing in own R&D. In the latter case, firms make use of external knowledge generated by other firms. For this, however, at least a share of the external knowledge must not be a private good (i.e., not appropriated by the owner). The magnitude of this share depends on the effectiveness of the mechanisms by which knowledge is protected - the appropriability conditions (Dosi, 1982). In the literature, there is a long discussion on the tradeoff between knowledge spillovers and appropriability conditions starting from Arrow (1962). It is argued that spillovers create a negative appropriability incentive. Reducing the innovation rent, large spillover possibilities result in lower (than optimal from a social point of view) level of R&D investments. However, due to the heterogeneity of companies, knowledge transfer via these spillovers contributes to technological progress and can be beneficial for recipient firms (de Fraja, 1993). Those spillovers are nevertheless only effective if the recipient of knowledge has a sufficient capacity to absorb it.

Absorptive capacity, that is the ability to value, assimilate and apply new knowledge, was originally conceptualised by CL as a byproduct of a firm's R&D efforts. By allowing the firm to complement its own knowledge with incoming spillovers, this capacity enhances a firm's problem-solving ability (Kim, 1998). Zahra and George (2002) extended the concept of absorptive capacity by differentiating between potential and realised absorptive capacity. Potential absorptive capacity involves the acquisition and assimilation of knowledge spillovers, while realised absorptive capacity guarantees the application of this knowledge through the development and refinement of routines that facilitate its transformation and exploitation.

As already hinted, spillovers generally arise from two sources: public and private R&D. Compared to public R&D, spillovers from private R&D are often not easily accessible. Moreover, in the context of today's rapidly changing and highly competitive business environment, spillovers from other firms' R&D often provide more relevant complementary resources. Firms often need to engage in cooperation with other firms to gain access to such knowledge spillovers. In this context, both dimensions of absorptive capacity are at work. Potential absorptive capacity helps the firm to identify an appropriate partner and learn from it, while realised absorptive capacity enables the firm to deploy the knowledge acquired in innovation which enhances profit. Indeed, recent empirical work on inter-firm learning and alliances has shown that firms with higher absorptive capacity tend to benefit more from external knowledge (e.g., de Jong and Freel, 2010; Lin et al, 2012).

When a firm engages in cooperation, in addition to involuntary spillovers from other organisations it can also appropriate voluntary spillovers from its partners (Gulati, 1998). But securing access to voluntary spillovers through partnerships has a potentially negative side effect because of the reciprocity that characterises cooperative arrangements. The (potential) partner's stock of knowledge creates an incentive to cooperate with that partner. But in exchange, it also needs to open up its own knowledge base (Fehr and Gächter, 2000). Consequently, spillovers from the firm's R&D efforts do not only reduce its own appropriation, they potentially improve its competitor's R&D performance.[4] This is a 'cost of partnership' which constitutes another form of the negative appropriability incentive. This negative incentive is lowered because the partner firm does not possess perfect absorptive capacity to appropriate all the spillovers (CL, p. 575-6; Hammerschmidt, 2009, p.426). Thus, what a firm worries about is not necessarily the total spillovers it generates, but how much its partner can absorb, that is, the effective spillovers which increase as the absorptive capacity of this (competing) partner increases.[5] Moreover, the firm also benefits from cooperation because it has access to a pool of knowledge larger than just its own, particularly when the partner holds complementary technological knowledge thereby creating a higher potential to innovate.

The relative value of knowledge spillovers can be represented by the distance between partners.[6] If the distance is small, companies well understand each other and there is much less uncertainty (Lane and Lubatkin, 1998), but there might be no new knowledge to learn and, hence, there is the risk of lock-in. In contrast, if the distance is large, the knowledge has higher novelty but is too difficult to absorb and coordination problems may arise (Boschma, 2005). This leads to the optimal cognitive distance hypothesis which has been the subject of many studies. The consensus in the empirical literature is that technological or cognitive proximity between cooperation partners has an inverted 'U'-shaped relation with the value of learning the partners obtain (or, alternatively, the

[4]This argument is important for our model and will be applied later in modeling the firm's profit.

[5]In our model we are concerned with firms competing on the same technological trajectory. In the extreme case that the cooperating partners operate in different industries, competition between them is mostly negligible. In this case, spillovers do not constitute a disincentive to cooperation and R&D investments (Cantner and Pyka, 1998, p. 374).

[6]Distance, in this sense, includes not only cognitive distance but also organisational, social, institutional and geographical ones (Wuyts et al, 2005; Boschma, 2005). For instance, Dettmann and von Proff (2010) demonstrated that organisational and institutional proximity facilitate long-distance collaboration in patenting. Similarly, Wuyts et al (2005) demonstrated that, depending on the industry, organisational and strategic proximity could be more important in the formation of alliances than the cognitive one. Nevertheless, since our study is concerned with knowledge sharing, it is more appropriate to concentrate on cognitive distance.

innovative potential of the alliance) (Lin et al, 2012; Gilsing et al, 2008; Nooteboom et al, 2007; Wuyts et al, 2005; Mowery et al, 1998). An understandability–novelty trade-off exists such that effective learning by interaction is better accomplished by limiting cognitive overlap while securing cognitive distance.

The discussion so far is based on a perception of absorptive capacity as a passive by-product of R&D investments made to generate inventions. However, it can be argued that the allocation of R&D resources is not a simple and unidirectional decision. A distinction can be made between absorptive R&D and inventive R&D. Absorptive R&D refers to the investments made to benefit from knowledge spillovers while inventive R&D is the effort made by a firm to generate original knowledge (Hammerschmidt, 2009; Cantner and Pyka, 1998). This distinction reflects the difference between "the exploration of new possibilities and the exploitation of old certainties" (March, 1991, p. 71)[7] as well as the common classification of R&D into basic and applied research. As Cassiman et al (2002) showed, by doing basic R&D a firm can effectively access incoming knowledge spillovers which then help to increase the efficiency of own applied R&D.

In this sense, absorptive capacity is no longer a passive by-product of R&D, but an explicit part of the firm's strategy. This strategic necessity is even more important when the external knowledge source (from which a firm desires to learn) is not close to its prior knowledge. This is also true when the knowledge, such as that which comes from universities and research institutes, is not directly applicable to the needs of the firm. In this case, CL (p. 572) argue that a firm's capacity to appropriate the knowledge increases as the firm invests more in R&D. This argument is extended with the distinction between inventive and absorptive R&D; it can now be noted that it is not routine R&D but explicit investments in the form of absorptive R&D that facilitates the build-up of absorptive capacity. At the same time, firms need to build up a certain level of capacity to generate own knowledge through inventive R&D.[8] Consequently, firms are faced with the strategic decision of how to optimally allocate resources between inventive and absorptive R&D, which, though complementary, are mutually exclusive. This constitutes an investment trade-off that holds important implications for a firm's learning abilities and cooperation preferences.

Historically, modeling studies have treated the R&D investment and cooperation decisions of firms only with respect to exogenous spillovers (see De Bondt, 1996, for an overview). Typically, such spillovers, especially when they are symmetric, have a negative effect on strategic R&D investments. At the same time, they incentivise firms to engage in cooperation and to make bilateral investment commitments. Later models account for absorptive capacity and show that technological heterogeneity, as reflected in relatively high (exogenous) spillover rates, incentivises the build-up of absorptive ca-

[7]Even in this framework the understandability–novelty trade-off exists. In the context of exploitation, wherein firms are concerned with improving their performance along the same technological trajectory, a high level of mutual understanding is required to reduce transaction costs (Drejer and Vindig, 2007; Cantner and Meder, 2007). Notwithstanding, since technological opportunities within a certain trajectory tend to decrease continuously according to Wolff's law (Cantner and Pyka, 1998), firms seek for more explorative or extensive opportunities, the aim of which is to generate novelty. Consequently, increasing cognitive distance positively influences the value of interactive learning because it raises the novelty value of technological opportunities as well as the possibility of novel combinations of complementary resources. This is, however, only possible as long as the partners are close enough to understand each other.

[8]This is a mechanism that assures the presence of reciprocal incentives for cooperation (Kamien and Zang, 2000; Wiethaus, 2005).

pacity (Hammerschmidt, 2009). Even when spillovers are endogenous, as is the case in the model of Cantner and Pyka (1998), adopting a strategy that allocates more resources to absorptive R&D as spillovers increase tends to be a more profitable strategy when compared with other strategies such as the one in which the firm concentrates purely on invention. A limitation of these studies is their failure to account for strategic alliance formation as a way for firms to access complementarities, pool knowledge resources or innovate jointly.

In more recent models (Cowan et al, 2007; Baum et al, 2010), alliance formation is driven by its probability to succeed in terms of knowledge generation and innovation, as well as the proximity of the potential partner. Among other things, the studies demonstrate that knowledge sharing is a major motivation for alliance formation. In particular, even in the absence of any social capital considerations[9], empirically founded network characteristics such as repeated alliances, transitivity and clustering can be observed. However, these models treat absorptive capacity as an exogenous parameter which is similar for all firms in the network. Although our model shares some of their features, an important contribution we make is that absorptive capacity is not modeled exogenously. In contrast, it is endogenous and is influenced by the two trade-offs described earlier. Ultimately, cooperation decision is driven by proximity considerations, endogenous absorptive capacity and the cost of partnership in terms of the knowledge spillovers that a potential partner can absorb.

3 The Model

In the model, firms compete within a defined knowledge space. A firm seeks to maximize its profit from generating innovations. It does this by developing absorptive capacity to gain from knowledge spillovers while also maintaining own inventive R&D. Consequently, the firm needs to decide how to allocate its R&D investments between own invention and the development of absorptive capacity. Knowledge spillovers are generated voluntarily through inter-firm cooperation and involuntarily. The decision on investment allocation is affected by cognitive distance (from both types of spillovers); larger distances correspond to higher resource heterogeneity or novelty potential but also to larger investments required to absorb them. In the static scenario that we analyse in this paper, the distances are given exogenously.[10] Each firm resolves the investment trade-off and makes a cooperation decision. This decision is influenced by cognitive distance, R&D investments and appropriability conditions. We are particularly interested in the conditions under which cooperation is superior to non-cooperation. To study this, we compare the R&D investments and profits for a cooperating and non-cooperating firm.

Some important assumptions are to be noted. Firstly, in making their cooperation decisions, firms consider only their short term potential profits. This assumption reflects firms' behaviour when the frontier of knowledge is rapidly extending, in which case the

[9]This means that technological fit, rather than social capital factors like trustworthiness and embeddedness, is a major causal force behind alliance formation (Baum et al, 2010). Firms will select partners from whom they can learn significantly and for specific (short-term) purposes. In this sense, multiple partnerships may not be necessary and firms stop their partnership search once they find a technologically fit partner.

[10]In a dynamic scenario, cognitive distance will change according to the innovation success of the firms. This consideration is beyond the scope of the present paper, but is considered in the companion work (Savin and Egbetokun, 2012).

pressure to innovate quickly is high, or when productive activities require a rapidly expanding knowledge base, in which case firms need to cooperate so as to gain access to complementary knowledge (Cowan et al, 2007).

Secondly, firms only select one partner and conduct one R&D project at a given period. This is a simplifying assumption that improves the tractability of the model, allowing us to focus exclusively on knowledge sharing between unique pairs of firms, and is computationally more feasible.

Thirdly, the reliability and trustworthiness of potential partners is not taken into account in the selection of cooperation partners. This follows partly from the short-termism with which firms approach partner selection. In addition, since the potential partners both have reciprocal incentives for cooperation, their likelihood to misbehave is significantly lower. Otherwise, firms can simply discontinue the partnership in the next period preventing an access to their voluntary spillovers.

Finally, firms are assumed to have perfect information about the knowledge base of other firms.[11] This assumption appears to be rather strong and is in contrast with the common perception that firms have imperfect information about partners' knowledge and motivations (Oxley, 1997). However, it finds justification in the fact that the capabilities and strategic focus of potential partners can be easily assessed through massive information that is freely available. For example, a firm's patent portfolio (which can be freely accessed online) contains significant information on its knowledge stock and market value (Hall et al, 2005). Thus, patents constitute a comprehensive representation of the knowledge space in an industry. Note also that investments in screening and understanding this knowledge (e.g., by hiring patent lawyers) can be considered as a separate share of a firm's R&D budget, further justifying the distinction in R&D investments applied in the model. In addition, there are several other channels through which reliable information can be obtained, for example, scientific and technical articles, hiring, and informal networks (see footnote 3 in Baum et al, 2010, for more details on this).

3.1 R&D investments

In accordance with CL, we consider R&D investments as an instrument to stimulate absorptive capacity. However, we consider this capacity to be not a by-product of the total R&D investments but of a separate share of it. Thus, we distinguish between investments directly in R&D that exploit identified technological opportunities (rdi_i) and investments for exploring the environment for technological development (aci_i), together forming total R&D spending (RD_i)[12]:

$$RD_i = rdi_i + aci_i = \rho_i RD_i + (1 - \rho_i) RD_i. \tag{1}$$

This investment tradeoff is shaped by learning incentives including the potential quantity and complexity of external knowledge.

[11] This does not necessarily eliminate the risks associated with innovation. First, firms need to be able to understand the available information, an endeavour which is by itself costly and risky. Then, innovation is still uncertain and runs the risk of failing, irrespective of how well-informed a firm's cooperation decisions are.

[12] We abstract from production and the market by treating the R&D budget RD_i as exogenous. In this way, the focus of the model is narrowed to the firm's investment decision, knowledge generation and innovation.

3.2 Knowledge generation

In line with CL, firm i's stock of knowledge in period t ($k_{i,t}$) is increased by a quantity comprising the firm's own direct investment in R&D and externally generated knowledge which, in turn, consists of other firms' R&D (rdi_k) and knowledge generated by public institutions (ek):

$$k_i = rdi_i^{\xi} + ac_i \left(\delta_n \sum_{k \neq i} rdi_k + ek \right), \tag{2}$$

where $\xi \in (0,1)$ is a parameter which defines the rate of return to inventive R&D, $\delta_n \in (0,1)$ reflects the fraction of knowledge not appropriated by companies[13] and $ac_{i,t} \in (0,1)$ is the degree to which firm i can absorb external knowledge, i.e. absorptive capacity. The summation term in (2) assumes no cooperation between firms, hence no voluntary knowledge spillovers. All firms want to ensure that the value of δ_n is as low as possible.

However, within a cooperative context the situation is different. Besides involuntary spillovers (δ_n), firm i can also appropriate voluntary spillovers (δ_c) from its strategic partner. Thus,

$$k_i = rdi_i^{\xi} + ac_i \left((\delta_c + \delta_n) \sum_{j \neq i} rdi_j + \delta_n \sum_{j \neq k \neq i} rdi_k + ek \right), \; 1 > \delta_c > \delta_n > 0$$

The term $\delta_c + \delta_n$ reflects total spillovers available to a cooperating firm and is always below 1. In a dyadic relationship, only one partner j is present, and it can be assumed that all involuntary spillovers available are included in the total external knowledge ek.[14] Therefore,

$$k_i = rdi_i^{\xi} + ac_i \left(\delta_c rdi_j + ek \right). \tag{3}$$

As it was stated above, we assume that firms have a perfect knowledge about the distances to their potential partners and about their R&D budgets. Now, since any particular firm takes a decision on the investments in R&D based on the investment decision of its potential partner, we assume that in any given period a firm considers the investment decision of the partner to be the same as in the previous period:

$$E^i(\rho_{j,t}) = \rho_{j,t-1}. \tag{4}$$

In this paper focusing on a static scenario, no interaction of firms is considered and the equality in (4) translates into an assumption of perfect knowledge also wrt the partner's investment trade-off (i.e., $E^i(\rho_j) = \rho_j$).[15]

[13] This fraction is determined by the appropriability conditions which include the patent system in a particular industry and the efficacy of secrecy or other forms of protection of firm j's internal knowledge

[14] This follows partly from our focus on dyadic partnerships. In this sense, knowledge spillovers from other firms not in the dyad and from public organisations together constitute technological opportunities for the dyad. Thus, the focus of our study is on voluntary spillovers while the involuntary ones are not ignored.

[15] However, in the dynamic case (Savin and Egbetokun, 2012) (4) necessarily introduces some uncertainty as the expectation of firm i will not necessarily coincide with the actual investment decision of firm j, which is based on its expactation about firm's i decision: $E^i(\rho_{j,t}) \neq \rho_j = f(E^j(\rho_{i,t}))$.

External knowledge, ek, is set as the total inventive R&D investment of other companies (N firms in total) in the knowledge space rescaled by the parameter of involuntary spillovers:

$$ek_t = \delta_n \sum_{i \neq k=2}^{N} rdi_{k,t}. \tag{5}$$

3.3 Absorptive capacity

Absorptive capacity (ac_i) is dependent on two variables: i) the distance ($d_{i.}$) between firm i's knowledge base and external knowledge available and ii) the investments in absorptive capacity (aci_i) made by the firm. Cognitive distance d_{ij} is modeled as an Euclidian distance between the stock of knowledge of the two partners i and j ($\nu_{i.}$ and $\nu_{j.}$), which are independently and randomly (uniform distribution) attributed to the firms over κ types of knowledge from the interval $[0, 1]$:

$$d_{ij} = \sqrt{(\nu_{i1} - \nu_{j1})^2 + (\nu_{i2} - \nu_{j2})^2}. \tag{6}$$

We take $\kappa = 2$ for a better visualization of results.[16]

As explained earlier, shared knowledge is the main motivation for alliance formation between any two firms i and j. Following Wuyts et al (2005), this knowledge can be represented as the mathematical product of its novelty value (which increases in cognitive distance) and understandability (that respectively decreases in cognitive distance):

$$an_{i,j} = (\alpha d_{ij})(\beta_1 - \beta_2 d_{ij}) = \alpha\beta_1 d_{ij} - \alpha\beta_2 d_{ij}^2, \tag{7}$$

And accounting for the stimulating role of investments in absorptive capacity (aci_i):

$$an_{i,j} = \alpha\beta_1 d_{ij}(1 + aci_i^{\psi}) - \alpha\beta_2 d_{ij}^2 = \alpha\beta_1 d_{ij} + \alpha\beta_1 d_{ij} aci_i^{\psi} - \alpha\beta_2 d_{ij}^2\,, \tag{8}$$

where $\psi \in (0, 1)$ reflects the efficiency of absorptive R&D. This investment essentially causes an upward shift in understandability for any given d_{ij} and has decreasing marginal returns. Since the aim of the firm is to maximise the knowledge it absorbs given its current level of absorptive capacity, we proceed by considering absorptive capacity as a function of the knowledge absorbed by i from cooperation with j. Specifically, it is presented as $an_{i,j}$ normalized by its maximum value:

$$ac_{i,j} = \frac{\alpha\beta_1 d_{ij} + \alpha\beta_1 d_{ij} aci_i^{\psi} - \alpha\beta_2 d_{ij}^2}{\frac{1}{4\alpha\beta_2}\left[\alpha\beta_1(1 + aci_i^{\psi})\right]^2} \in [0, 1] \tag{9}$$

A larger d_{ij} increases the marginal impact of aci_i on absorptive capacity ($\frac{\partial ac_{i,j}}{\partial aci_i \partial d_{ij}} > 0$), which corresponds with CL (p. 572).[17] In contrast, the effect of d_{ij} on $ac_{i,j}$ is ambigu-

[16] Here we consider this distance to be given exogenously and fixed over time. In a separate dynamic analysis we allow the distance to vary depending on cooperation intensity.

[17] Note that while cognitive distance is symmetric (i.e. $d_{ij} = d_{ji}$), $an_{i,j}$ and $ac_{i,j}$ are asymmetric. This is because the investment trade-off is not solved by the two companies identically (i.e. absorptive R&D investments are not necessarily the same for the two companies).

ous: for a given value of aci_i, it is positive ($\frac{\partial ac_{i,j}}{\partial d_{ij}} > 0$ and $\frac{\partial^2 ac_i}{\partial d_{ij}^2} < 0$) until a certain optimal distance is reached and negative ($\frac{\partial ac_i}{\partial d_{ij}} < 0$) otherwise (Figure 1). The maximum of the inverted 'U'-shaped function shifts right (left) with increasing (decreasing) aci_i (Figure 2), allowing a firm to adopt its absorptive capacity to the actual distance from its cooperation partner. The latter characteristic corresponds to the empirical fact that investments in absorptive capacity raise the optimal distance between cooperation partners (de Jong and Freel, 2010; Drejer and Vindig, 2007).

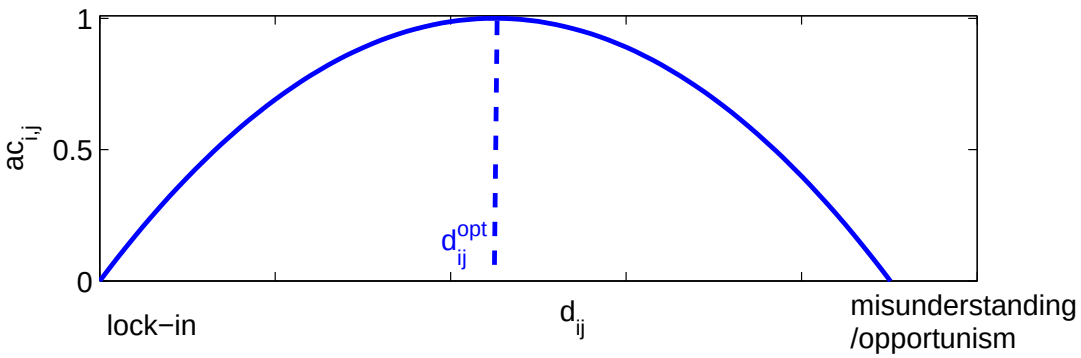

Figure 1: Absorptive capacity function

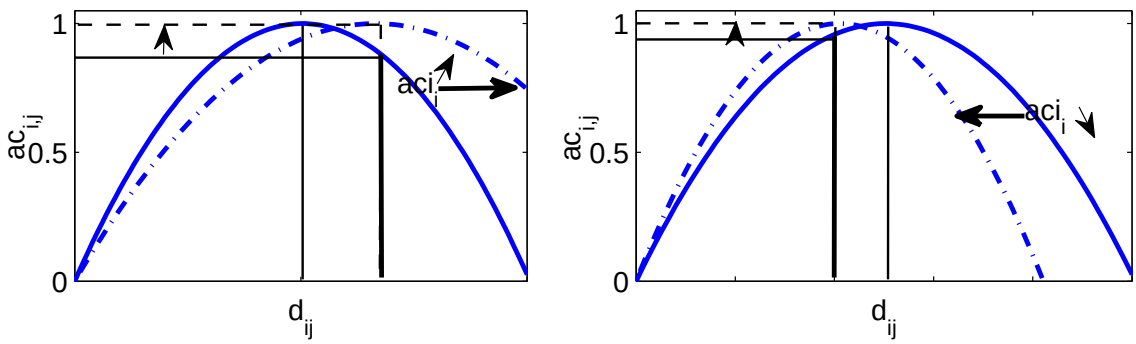

Figure 2: Dynamics in absorptive capacity function

Note: As company i increases its investments in absorptive capacity (aci_i), the optimal distance to its cooperating partner increases. Thus, for the larger distance, i has a higher absorptive capacity by increasing its investments (left plot). The opposite is true for the lower distance (right plot).

It is clear from (9) that when $d_{i.} = 0$ absorptive capacity equals zero. This is because if there is no difference between firm i's own knowledge and the external one, the novelty value is zero even if understandability is maximal. In this way, absorptive capacity ($ac_{i,.}$) is modeled explicitly at the level of interactive learning;[18] and it captures not only the ability to understand external knowledge, but also the ability to explore the environment and to identify novel knowledge.

It should be noted that the cognitive distance of firm i from from external knowledge ek (i.e. d_{iek}) is not necessarily the same as that from firm j (i.e. d_{ij}). In this study we consider it as the average distance to all other firms in the knowledge space:

[18]This is similar to the conceptutalisation by Lane and Lubatkin (1998) of absorptive capacity as 'a learning dyad-level construct'.

$$d_{iek,t} = \frac{\sum_{i \neq k=2}^{N} d_{ik}}{N}, \tag{10}$$

so that the maximum distance to the external knowledge does not exceed the maximum distance to a single potential partner in this space. Thus, for the same level of absorptive R&D, the absorptive capacity directed on each of the two sources of spillovers will be different.[19] When this is accounted for, (3) transforms into:

$$k_i = rdi_i^{\xi} + ac_{i,j}\left(\delta_c rdi_j\right) + ac_{i,ek}\left(ek\right). \tag{11}$$

Without an R&D partner, the knowledge to be generated by firm i is different (ek is the only source of external knowledge):

$$k_i^{\text{generated alone}} = rdi_i^{\xi} + ac_{i,ek}\left(ek\right) \text{ as } \delta_c = 0. \tag{12}$$

3.4 Innovation and profit

Innovation is perceived as a process which involves recombination of heterogeneous resources. Thus, the size of a potential innovation (if it is successful) is defined by the amount of knowledge (k_i) generated. The profit (Π_i) realised by the firm is dependent on the probability to innovate (Θ). This probability is treated as exogenous and reflects the uncertainty of the innovation process (Dosi, 1988; Utterback and Abernathy, 1975).[20] When the firm does not form a partnership, its profit is not affected by voluntary spillovers. In a partnership, however, the profit of the firm decreases proportionally with the amount of knowledge spillovers ($ac_{j,i}\delta_c rdi_i$) that the partner can absorb (which is essentially a constituent part of k_j that reduces the appropriability of k_i). This is in contrast to CL where Π_i is reduced proportional to the knowledge generated by the partner (k_j).[21] This 'cost of partnership' or, in the words of CL, 'effect of rivalry' affects the choice of an R&D partner. To avoid the problem of increasing Π_i for $ac_{j,i}\delta_c rdi_i < 1$, we introduce a 'natural' leak-out that is fixed and equal to 1.

$$\Pi_i = \begin{cases} \Theta \frac{k_i}{1+ac_{j,i}\delta_c rdi_i} & \text{if } i \text{ has a partner } j, \\ \Theta k_i^{\text{generated alone}} & \text{if } i \text{ has no partner.} \end{cases} \tag{13}$$

One way of interpreting the profit function in case of partnership in (13) is a split of property rights over a certain invention (new technology) converted into a monetary value. Since this technology may be used in different applications, the split is not necessarily exact; however, appropriation of rights over the invention is reduced by the amount of spillovers to a competing partner. Thus, the form of the function suggested can have a meaningful (although not necessarily exclusive) economic interpretation and also follow the assumptions on the functional form from CL (see above).

[19] As in (9), $ac_{i,ek} = f(d_{iek})$.

[20] For example, this probability of innovation success can be considered binary with a lognormal distribution $\Theta \sim \ln\mathcal{N}(\mu, \sigma^2)$ to ensure the event of innovation in any given period to be low (e.g., one innovation at any given period at maximum).

[21] Recall that in CL $\frac{\partial \Pi_i}{\partial k_i} > 0$, $\frac{\partial \Pi_i}{\partial k_j} < 0$ and $\frac{\partial \Pi_i}{\partial k_i \partial k_j} < 0$.

4 Optimal decision making

In the following we discuss the optimal strategy of firm i in i) solving the investment trade-off and ii) forming a partnership. Our interest is in how absorptive capacity (derived from R&D resource allocation, ρ_i), cognitive distance (d_{ij}), appropriability conditions (δ_c) and technological opportunities (ek) affect the benefits from cooperation. To study this, we resolve the investment trade-off for a representative firms in two scenarios (cooperative and non-cooperative) and compare the results in terms of innovative profit.

4.1 Investment trade-off

For certain levels of the distance d_{ij} that maximises understandability and novelty, firm i is incentivised to invest in absorptive R&D to maximise the amount of external knowledge absorbed. The trade-off that the firm faces is how to optimally distribute its total R&D investment between the creation of own knowledge and the improvement of absorptive capacity. This necessitates a comparison of the marginal returns to each type of investment with respect to the profit gained. Absorptive R&D begins to pay off when it generates a marginal return that is equal to that of inventive R&D:

$$\frac{\partial \Pi_i}{\partial aci_i} = \frac{\partial \Pi_i}{\partial rdi_i} \tag{14}$$

Using (13), (12), (11), (9) and (1), we obtain (see Appendix 1 for derivation) the condition for the R&D investment that satisfies (14):

$$\begin{cases} \mathrm{F}(\rho_i) = 0 & \text{if } i \text{ has a partner } j, \\ \mathrm{F}^{\mathrm{a}}(\rho_i) = 0 & \text{if } i \text{ has no partner.} \end{cases} \tag{15}$$

As (15) is a highly complex non-linear function with multiple local minima depending on the particular set of parameter values applied, it is a non-trivial problem to find the value of ρ_i satisfying the condition.[22] For this reason we apply a heuristic optimisation technique, in particular, Differential Evolution that is able to identify a good approximation of the global optimum in (15) for different sets of calibrating parameters as long as they satisfy the conditions stated above (see Appendix 2 for details).

4.2 Partnership formation

Since larger distances (until a certain optimum level) increase the marginal returns to new knowledge generated, it follows that each firm prefers to select a cooperation partner at the largest distance possible to maximise the novelty value of the R&D cooperation. At the same time, the partner choice is essentially constrained by understandability such that the firm i chooses a partner which it can also understand. In addition, the firm also takes into account the costs of partnership as a result of spillovers from its R&D efforts. Ultimately, the decision to cooperate (or not) is a profit-maximising one which depends

[22] A deterministic iterative solution (e.g., according to the fixed-point theorem) is also not applicable as the function does not necessarily always converge to a $\rho_i \in [0, 1]$ for all possible combinations of parameters.

on the potential profit generated when working alone in comparison with profit generated by cooperating with the most 'fitting' partner:

$$\max\left(\Pi_i^{\text{generated alone}}; \Pi_i^{\text{with any of the possible partners}}\right). \tag{16}$$

To this end, the simulation in the basic case can proceed as follows. First, all exogenous parameters (α, β_1, β_2, ψ, ξ, η, γ, ρ_j, δ_c, ek (the latter three variables can be simulated with different scenarios)) must be set.[23] This also includes a random distribution of the initial stocks of knowledge ($\Rightarrow$ set d_{ij}) and aggregated R&D budgets (RD) for all firms.

Second, in each period one needs to solve the investment trade-off of each company ($\rho_.$) for all potential partners, considering the expectation about other firms' investments in R&D to be known. After that, the amount of knowledge $k_.$ to be generated by each company either alone (standalone mode) or in partnership with any of the firms in the knowledge space is estimated. Based on this information the most lucrative partner for each company can be selected by maximizing profit from R&D activity Π_i: $\max(\Pi_i^{alone}, \Pi_i^j, ...) = \max(\Theta k_{i,t}, \Theta \frac{k_{i,t}}{1+ac_{j,i,t}\delta_c rdi_{i,t}}, ...)$.

Third, although the most lucrative partner for each firm is identified, partnership formation is a non-trivial task in this model. The reason is that the incentives of a firm i to build a partnership with firm j are asymmetric: although distance between the partners is the same, the decision on the investment trade-off in R&D is individual for each company. Hence, there is no 'Nash stable network' [24]. So far, we consider few alternatives on forming partnerships:

- *A rule of thumb*: if firm i identifies firm j as the most lucrative cooperation partner and is itself among the 'top' 10% of the companies with whom firm j would cooperate, then they build a partnership. The main advantage of the method is its simplicity and low computational time required.

- *A 'popularity contest'*: one counts for how many firms each company is the most lucrative one, the second most lucrative one, ... After that the firms are ranked according their popularity and choose themselves a partner in the order of this ranking. Computational cost of this approach is slightly higher, but the sceanario may be considered as a more realistic one.

- *An algorithmic search*: first, we exclude all firms out of the further search, which in any case prefer 'standing alone' (no cooperation); then we randomly select a company i out of the population and identify its most lucrative partner j. If for j it is the same (i.e., i is the most lucrative), they form a partnership and are excluded from further search. If it is not the case, we continue with j searching for its most

[23] For illustrative reasons we take a single set of parameter values for two firms satisfying their constraints. In particular, $\alpha = \sqrt{2}/50$, $\beta_1 = \sqrt{2}$, $\beta_2 = 1$, $\psi = 0.3$, $\xi = 0.5$, $RD_i = RD_j = 4$, $\delta_c = 0.75$, $ek = 1$, $\rho_j = 0.5$ and $d_{iek} = \sqrt{2}/1.01$. These values were chosen to demonstrate on a single set of graphs the complex shape of the ρ and Π functions in response to changes in the variables of interest.

[24] 'a stable network is one in which for each agent (or pair of agents) there is a payoff maximizing decision about which link to form' (Cowan et al, 2007, p. 1052)

lucrative partner. If the search path becomes cyclical ($i \to j \to k \to i...$), we exclude the entire cycle (none of the firms builds a partnership) and continue the random search. Computational time in this case is the highest (increases exponentially with the number of firms in the population), but may be also argued as a realistic scenario of partnership formation.

It remains for simulation experiments to decide which of the scenarios described fits best. After that the companies' profits based on realised innovation success (Θ) can be estimated. The algorithm may run from 1 to T periods. Since in the static scenario only exogenous parameters may change from period to period (distances in the knowledge space are not recalculated), the extensive simulation is left for the dynamic approach described in the companion paper of this study (Savin and Egbetokun, 2012). In the following, only some illustrative results for one firm in two scenarios (cooperative and non-cooperative) are demonstrated.

4.3 Comparative statics

In CL, absorbed external knowledge is endogenous and influenced by R&D investments, which is itself affected by the ease of learning, intra-industry spillovers and technological opportunities.[25] The effects of the latter group of parameters are similar for both R&D investment and the payoff it generates for the firm. However, the extensions we make in our study imply different results. First, the distinction between absorptive (aci_i) and inventive (rdi_i) R&D implies that the learning effects of R&D are only driven by investments in absorptive R&D. Second, explicitly accounting for voluntary spillovers implies that reciprocal incentives are involved. Thus, besides its own resource allocation problem, firm i takes into account the investment decisions of the potential partner firm j.

Moreover, in contrast to CL, we model in the context of inter-firm cooperation and so we concentrate on innovation-driven profit and cooperation decision rather than just on R&D investments. As it is clear from comparing (1) and (13), the parameter effects on the firm's R&D investments ($\partial RD_i/\partial \cdot$) and its payoff in terms of profit ($\partial \Pi_i/\partial \cdot$) are not necessarily similar. In Table 1 we summarise our results in comparison to CL[26] focusing on the latter group of effects (as the R&D profit presents the main motivation for firms to engage in cooperation in our study), while Figure 3 illustrates them in detail for the cooperating and non-cooperating scenarios.

[25]For the sake of comparison, CL's ease of learning is analogous to our cognitive distance construct, intra-industry spillovers - to appropriability conditions and technological opportunities - to total external knowledge.

[26]Note that by construction, in CL firm i's marginal returns to R&D have the same effect on marginal returns generated by the firm in terms of profit.

Table 1: Comparative static results

Effect	CL	Our model
$\partial\Pi_i/\partial d_{ij}$	positive	ambiguous
$\partial\Pi_i/\partial\delta_c$	ambiguous	ambiguous
$\partial\Pi_i/\partial\rho_j$	-	positive
$\partial\Pi_i/\partial ek$	ambiguous	positive

4.3.1 Cognitive distance

As seen from the bottom leftmost plot in Figure 3, the cognitive distance d_{ij} between cooperating partners has an ambiguous effect on R&D profits. A small distance (which does not require absorptive investments) positively affects R&D profit. This is because the firm can dedicate most of its R&D budget to invention and it suffers little or no negative appropriation in return (top leftmost plot). However, as distance increases the firm has to invest in absorptive capacity to maintain its gain from the partner's knowledge. This causes a reduction in inventive R&D, and by implication, in R&D profit since the cost of partnership in terms of spillovers also increase. At a very large distance, an 'understandability problem' arises such that the new knowledge cannot be absorbed as efficiently any longer and firm i cannot compensate it with sufficient investments in absorptive capacity. As a result, the firm may shift some of its resources back to inventive R&D.

Taken together, these results imply that firms choose a cooperation partner conditional on the investments they are ready to make in order to establish efficient collaboration. And in contrast to CL, where the ease of learning has a strictly positive effect on R&D investments and profit when cooperation is not accounted for, the effect of cognitive distance on profit has an inverted 'U' shape in the context of cooperation. In comparison, with the same set of parameters one can conclude that the standalone strategy is more lucrative when the distance to a potential partner is either too large (understandability problem) or too small (no novelty).

4.3.2 Appropriability conditions and external knowledge

With regard to both δ_c and ek, the situation is different. $\partial k_i/\partial\delta_c$ and $\partial k_i/\partial ek$ are strictly positive suggesting that the appropriability conditions in a cooperative setting (δ_c) as well as the amount of external knowledge (ek) raise the ability of the firm i to create new knowledge from external sources. Consequently, firm i is incentivised to reallocate its investments from inventive to absorptive R&D. More resources are devoted to absorptive capacity which generally results in a higher level of new knowledge (k_i) generated from the cooperation. However, in contrast to ek (which has a strictly positive effect on R&D profit), δ_c also contributes to the spillovers the cooperating partner can potentially absorb from i, reducing its R&D profit. Thus, starting from a certain level, firm i's losses from a larger δ_c can exceed its benefits. This ambiguous inverted 'U'-shaped relation of Π_i to δ_c is necessarily affected by the absorptive R&D budget of the partner: if it is small enough, firm i can benefit from intensive cooperation not being afraid that its partner absorbs much.

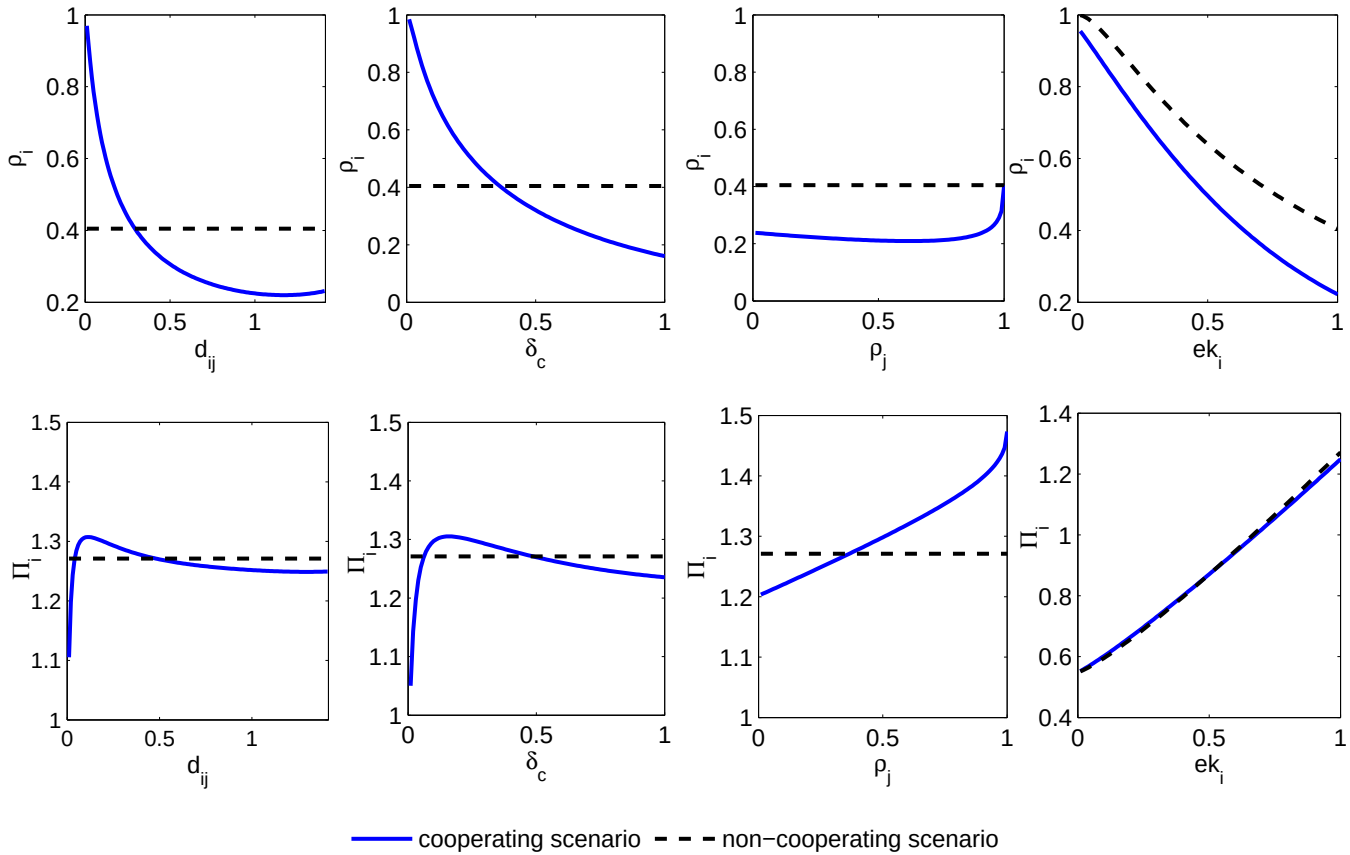

Figure 3: Comparative statics for the investments (ρ_i) and profits (Π_i) of firms

This particular result contrasts with CL where the effect of appropriability conditions is modified by the ease of learning. In our model, the effect of cognitive distance in this respect is captured in absorptive capacity which has the inverted 'U'-shaped form representing the understandability/novelty trade-off. With a very large cognitive distance the appropriability conditions may not matter at all as the partners have difficulties understanding each other. Again, in comparison, we find that the non-cooperative strategy is more lucrative when the cooperation intensity is either too large (threat of large spillovers) or too small (the additional external knowledge is too small to invest in it).

Since technological opportunities are equally available for both cooperating and non-cooperating firms, R&D profit in relation to ek is only dependent on the firm's absorptive capacity (see equation (12)); and it varies due to the different number of factors involved - for the cooperating and non-cooperating scenarios - in the firm's optimal decision making (see Appendix 1).

4.3.3 R&D investments and absorptive capacity

Finally, the investment decision of the partner ρ_j has an ambiguous effect on firm i's investment allocation, but not on its profit (where it is strictly positive). This is because as ρ_j increases, it contributes to the pool of external knowledge i can benefit from. This creates an incentive to increase investments in absorptive capacity. However, for ρ_j reaching its maximum values (close to 1) the cooperating partner lowers its absorptive capacity to a very small extent. Thus, knowledge spillovers from firm i to firm j that can be absorbed do not present a big threat for firm i's inventive R&D any longer leading to a large change in the firm's investment allocation and, subsequently, its R&D profit. Hence, the non-cooperative strategy is more lucrative only when the partner mostly invests in absorbing knowledge and not in its generation ('free rider' problem).

5 Conclusion

In this paper we set out to model absorptive capacity within the framework of inter-firm cooperation such that the capacity of a firm to appropriate external knowledge is not only a function of its R&D efforts but also of the distance from its partner. This framework allows us to account for recent empirical observations and to examine factors affecting the choice of a firm on whether to engage in R&D cooperation or not. Our analysis is concentrated on cognitive distance though other kinds of distance are also important. In this paper we analyse the static case, where the cognitive distance between cooperating firms is fixed and given exogenously, while the dynamic approach, where distance varies as a function of the intensity of cooperation between partners, is considered in a companion paper (Savin and Egbetokun, 2012).[27]

Comparing the results obtained with the original model of Cohen and Levinthal (1989) shows some clear differences. First of all, the cognitive distance between a firm and its cooperation partner has an ambiguous effect on the profit generated by the firm. Thus, a firm chooses its cooperation partner conditional on the investments in absorptive capacity it is willing to make to solve the understandability/novelty trade-off. Hence, firms

[27] In the dynamic case, it is expected that a firm will reconsider its cooperation decisions depending on cognitive distance. Alliances may be discontinued when partners become too close and previously discontinued alliances may be re-formed if the partners have become sufficiently distant in terms of their knowledge endowment. A simulation experiment to demonstrate this dynamics is in progress.

possessing a larger R&D budget have a possibility to engage in cooperation with firms located further away in terms of cognitive distance. If the partner is too close or too far, no efficient colloboration can be established.

Next, though appropriability conditions in the framework of cooperation also have an ambiguous effect on profits, this effect does not necessarily become greater (positive) with a larger cognitive distance as in CL.[28] At a very large cognitive distance the appropriability conditions may not matter at all as the partners cannot understand each other. In contrast, the question is: how large is the partner's absorptive capacity? In our formulation, absorptive capacity is a more complex construct presenting the interaction between a firm's absorptive R&D and cognitive distance. The larger the partner's absorptive capacity, the larger the portion of knowledge spillovers that this partner can assimilate. This complex ambiguity, from our view, partly explains the caution that firms have in engaging in R&D cooperation and the very detailed contracts related to the respective agreements (see, e.g., Atallah (2003)).

Finally, external knowledge, that is knowledge available outside the framework of cooperation, as well as the partner's inventive R&D investments have positive effects on the R&D profit. While the latter distinguishes our model from CL (where such a variable is not explicitly considered), the former demonstrates an effect that somehow contradicts CL. The reason is that according to CL where R&D investments are considered as one expense item, external knowledge reduces incentives to own R&D on the one hand, but incentivises investments for absorptive capacity on the other hand. Since we distinguish between inventive and absorptive R&D, the dynamics from CL is contained in the upper rightmost plot in Figure 3 (i.e. reaction in investment allocation), while the total effect on the R&D profit is strictly positive. Also it is clear that the knowledge about the partner's R&D investment allocation presents an important asset for any firm in our model. Ability to foresee this split allows a company to avoid opportunistic behaviour from potential partners (i.e. 'free riders' with low inventive R&D) and better resolve the two trade-offs in their decision making (optimal cognitive distance and optimal split of investments). For an explicit account of uncertainty about this information as well as for more simulation results, see Savin and Egbetokun (2012).

Appendix 1

Resolving the investment trade-off (equation 14) to find ρ_i

The objective is to obtain values of ρ_i that satisfy:

$$\frac{\partial \Pi_i}{\partial aci_i} = \frac{\partial \Pi_i}{\partial rdi_i}.$$

Recall from (13) that in case of a partnership, where i needs to optimise its investment allocation conditional upon the partner's investments,

$$\Pi = \Theta \frac{k_{i,t}}{1 + ac_{j,i,t}\delta_c rdi_{i,t}}.$$

[28] In CL the effect of appropriability conditions is modified by the ease of learning.

The time argument is dropped since for now we consider the static scenario:

$$\frac{\partial \Pi_i}{\partial rdi_i} = \frac{\partial(\frac{k_i}{1+ac_{j,i}\delta_c rdi_i})}{\partial rdi_i} = \frac{\xi rdi_i^{\xi-1}(1+ac_{j,i}\delta_c rdi_i) - k_i\delta_c ac_{j,i,t}}{(1+ac_{j,i}\delta_c rdi_i)^2}, \tag{17}$$

$$\frac{\partial \Pi_i}{\partial aci_i} = \frac{\partial\left(\frac{k_i}{1+ac_{j,i}\delta_c rdi_i}\right)}{\partial aci_i} = \frac{(1+ac_{j,i}\delta_c rdi_i)\left(\frac{\partial k_i}{\partial ac_i}\right) + k_i\delta_c ac_{j,i}}{(1+ac_{j,i}\delta_c rdi_i)^2}, \tag{18}$$

where $E^i(\rho_{j,t}) = \rho_{j,t-1} \Rightarrow \frac{\partial ac_{j,i}}{\partial rdi_i} = 0$ and $rd_i = RD_i - aci_i \Rightarrow \frac{\partial rdi_i}{aci_i} = -1$. Next we set (17) equal to (18) as in equation (14):

$$\xi rdi_i^{\xi-1}(1+ac_{j,i}\delta_c rdi_i) - k_i\delta_c ac_{j,i,t} = (1+ac_{j,i}\delta_c rdi_i)\left(\frac{\partial k_i}{\partial ac_i}\right) + k_i\delta_c ac_{j,i}$$

and collect terms:

$$\frac{\xi rdi_i^{\xi-1}}{\left(\frac{\partial k_i}{\partial ac_i}\right)} = \frac{2k_i\delta_c ac_{j,i}}{(1+ac_{j,i}\delta_c rdi_i)}. \tag{19}$$

Recalling the expression for k_i from (11) we obtain

$$\frac{\partial k_i}{\partial ac_i} = \delta_c rdi_j\left(\frac{\partial ac_{i,j}}{\partial aci_i}\right) + ek\left(\frac{\partial ac_{i,ek}}{\partial aci_i}\right). \tag{20}$$

Accounting for the difference in d_{ij} and d_{iek} in $ac_{i,\cdot}$ (9) we obtain the derivative of the absorptive capacity function with respect to distance as follows:

$$\frac{\partial ac_{i,\cdot}}{\partial aci_i} = \frac{4\beta_2\psi d_{i\cdot} aci_i^{\psi-1}}{\beta_1(1+aci_i^{\psi})^2}\left[\frac{2\beta_2 d_{i\cdot}}{\beta_1(1+aci^{\psi})} - 1\right]. \tag{21}$$

Inserting (21) into (20) accordingly:

$$\begin{aligned}\frac{\partial k_i}{\partial ac_i} &= \delta_c rdi_j\left(\frac{4\beta_2\psi d_{ij} aci_i^{\psi-1}}{\beta_1(1+aci_i^{\psi})^2}\left[\frac{2\beta_2 d_{ij}}{\beta_1(1+aci^{\psi})} - 1\right]\right) \\ &+ ek\left(\frac{4\beta_2\psi d_{iek} aci_i^{\psi-1}}{\beta_1(1+aci_i^{\psi})^2}\left[\frac{2\beta_2 d_{iek}}{\beta_1(1+aci^{\psi})} - 1\right]\right).\end{aligned} \tag{22}$$

Note that the absorptive capacity of firm j directed on firm i is:

$$ac_{j,i} = \frac{\alpha\beta_1 d_{ij} + \alpha\beta_1 d_{ij} aci_j^{\psi} - \alpha\beta_2 d_{ij}^2}{\frac{1}{4\alpha\beta_2}\left[\alpha\beta_1(1+aci_j^{\psi})\right]^2} \quad \text{as} \quad d_{ij} = d_{ji}. \tag{23}$$

When (22) and (23) are inserted in (19) and the latter is rearranged, we obtain

$$
\begin{aligned}
rdi_i \;=\; & \frac{32\beta_2^2}{\xi\alpha\beta_1^4\left(\beta_1+\beta_1 aci_j^{\psi}-\beta_2 d_{ij}\right)\left(1+aci_i^{\psi}\right)^5}\Bigg(\delta_c rdi_j d_{ij}\left(2\beta_2 d_{ij}-\beta_1\left(1+aci_i^{\psi}\right)\right)\;+ \\
& +\; ekd_{iek}\left(2\beta_2 d_{iek}-\beta_1\left(1+aci_i^{\psi}\right)\right)\Bigg)\frac{aci_i^{\psi-1}}{rdi_i^{\xi-1}}\left(\beta_1+\beta_1 aci_j^{\psi}-\beta_2 d_{ij}\right)\cdot \\
& \cdot\Bigg(\frac{rdi_i^{\xi}}{4\alpha\beta_2}\left(\alpha\beta_1\left(1+aci_i^{\psi}\right)\right)^2\;+\;\alpha\delta_c rdi_j d_{ij}\left(\beta_1+\beta_1 aci_i^{\psi}-\beta_2 d_{ij}\right)\;+ \\
& +\;\alpha d_{iek} ek\left(\beta_1+\beta_1 aci_i^{\psi}-\beta_2 d_{iek}\right)\Bigg)-\frac{\beta_1\left(1+aci_j^{\psi}\right)^2}{4\beta_2\delta_c d_{ij}\left(\beta_1+\beta_1 aci_j^{\psi}-\beta_2 d_{ij}\right)}.
\end{aligned}
\tag{24}
$$

Recall from (1) that $rdi_i = \rho_i RD_i$ and $aci_i = (1-\rho_i)RD_i$; when this is applied to equation (24) it takes the form:

$$
\begin{aligned}
\rho_i \;=\; & \frac{32\beta_2^2}{\xi\alpha\beta_1^4 RD_i\left(\beta_1+\beta_1\left((1-\rho_j)\,RD_j\right)^{\psi}-\beta_2 d_{ij}\right)\left(1+\left((1-\rho_i)\,RD_i\right)^{\psi}\right)^5}\cdot \\
& \cdot\Bigg(\delta_c\rho_j RD_j d_{ij}\left(2\beta_2 d_{ij}-\beta_1\left(1+\left((1-\rho_i)\,RD_i\right)^{\psi}\right)\right)+ \\
& +\;ekd_{iek}\left(2\beta_2 d_{iek}-\beta_1\left(1+\left((1-\rho_i)\,RD_i\right)^{\psi}\right)\right)\Bigg)\frac{(1-\rho_i)^{\psi-1}\,RD_i^{\psi-\xi}}{\rho_i^{\xi-1}}\;\cdot \\
& \cdot\left(\beta_1+\beta_1\left((1-\rho_j)RD_j\right)^{\psi}-\beta_2 d_{ij}\right)\Bigg(\frac{(\rho_i RD_i)^{\xi}}{4\alpha\beta_2}\left(\alpha\beta_1\left(1+\left((1-\rho_i)RD_i\right)^{\psi}\right)\right)^2\;+ \\
& +\;\alpha\delta_c\rho_j RD_j d_{ij}\left(\beta_1+\beta_1\left((1-\rho_i)RD_i\right)^{\psi}-\beta_2 d_{ij}\right)\;+ \\
& +\;\alpha d_{iek} ek\left(\beta_1+\beta_1\left((1-\rho_j)RD_j\right)^{\psi}-\beta_2 d_{iek}\right)\Bigg)\;- \\
& -\;\frac{\beta_1\left(1+\left((1-\rho_j)RD_j\right)^{\psi}\right)^2}{4\beta_2\delta_c d_{ij} RD_i\left(\beta_1+\beta_1\left((1-\rho_j)RD_j\right)^{\psi}-\beta_2 d_{ij}\right)}.
\end{aligned}
\tag{25}
$$

Shifting ρ_i from the left hand side to the right one, one gets $\mathrm{F}(\rho_i) = 0$.

Remembering that for firm i performing R&D activity without a partner $\delta_c = 0$, it is straightforward to show that for this firm (25) takes a simpler form as follows:

$$
\begin{aligned}
F^a(\rho_i) \;&= ek\frac{4\beta_2\psi d_{iek}((1-\rho_i)RD_i)^{\psi-1}}{\beta_1(1+((1-\rho_i)RD_i)^{\psi})^2}\left(\frac{2\beta_2 d_{iek}}{\beta_1(1+((1-\rho_i)RD_i)^{\psi})}-1\right)- \\
&-\;\xi\,(\rho_i RD_i)^{\xi-1}=0.
\end{aligned}
\tag{26}
$$

Appendix 2

Finding optimal solution for $F(\rho_i)$ and $F^a(\rho_i)$ using heuristics

Thanks to the recent advances in computing technology, new nature-inspired optimization methods (called heuristics) tackling complex combinatorial optimization problems and detecting global optima of various objective functions have become available (Gilli and Winker, 2009). Differential Evolution (DE), proposed by Storn and Price (1997), is a population based optimization technique for continuous objective functions. In short, starting with an initial population of solutions, DE updates this population by linear combination and crossover of four different solutions into one, and selects the fittest ones among the original and the updated population. This continues until some stopping criterion is met. Algorithm 1 provides a pseudocode of the DE implementation.

Algorithm 1 Pseudocode for Differential Evolution

1: Initialize parameters p, F and Ω
2: Randomly initialize $P_i^{(1)} \in \Omega$, $i = 1, \cdots, p$
3: **while** the stopping criterion is not met **do**
4: $\quad P^{(0)} = P^{(1)}$
5: $\quad$ **for** $i = 1$ to p **do**
6: $\quad\quad$ Generate r_1,r_2,r_3 $\in 1, \cdots, p$, $r_1 \neq r_2 \neq r_3 \neq i$
7: $\quad\quad$ Compute $P_i^{(v)} = P_{r_1}^{(0)} + F \times (P_{r_2}^{(0)}$ - $P_{r_3}^{(0)})$
8: $\quad\quad$ **if** $P_i^{(v)} \in \Omega$ **then** $P_i^{(n)} = P_i^{(v)}$ **else** *repair* $P_i^{(v)}$
9: $\quad\quad$ **if** $F(P_i^{(n)}) < F(P_i^{(0)})$ **then** $P_i^{(1)} = P_i^{(n)}$ **else** $P_i^{(1)} = P_i^{(0)}$
10: $\quad$ **end for**
11: **end while**

In contrast to other DE applications to optimization problems (as described in, for example, Blüschke et al, 2012), our solution is represented by a single value within $[0, 1]$ according to (1). Therefore, DE starts with a population of size p of random values drawn from $[0, 1]$ (Ω) (2:). For the same reason, current DE implementation has no need in the crossover operator (otherwise, one would have to compare $F(P_i^{(0)})$ with itself and potentially waste computational time). Tuning our DE code we set $p = 30$, $F = 0.8$ and as a stopping criterion we choose a combination of two conditions: either a maximum number of generations is reached (which is set to be equal 50[29]) or the global optimum is identified ($F(P_i^{(1)}) = 0$). To make sure that our candidate solutions constructed by linear combination (7:) satisfy our constraint on ρ_i, we explicitly check it in (8:) - and if it is not met we 'repair' it by adding/deducting one unit - before comparing its fitness with the current solutions in (9:).

As an illustration of the DE convergence for the tuning parameters stated consider Figure 4 below. On the left plot one can see $F(\rho_i)$ simulated for different $\rho_i \in [0, 1]$, while on the right plot the cumulative density function of $F(\rho_i)$ for 100 restarts and different number of maximum generations g (10, 30 and 50) is given. Obviously, with $g = 50$ DE converges to zero (or a very close approximation of it) in almost 100% of restarts. To ensure a good solution, therefore, we take $g = 30$ and restart DE three times. Using Matlab 7.11 on Pentium IV 3.3 GHz a single DE restart with thirty generations requires about 0.02 second.

[29] At this point DE population always converges to very similar values

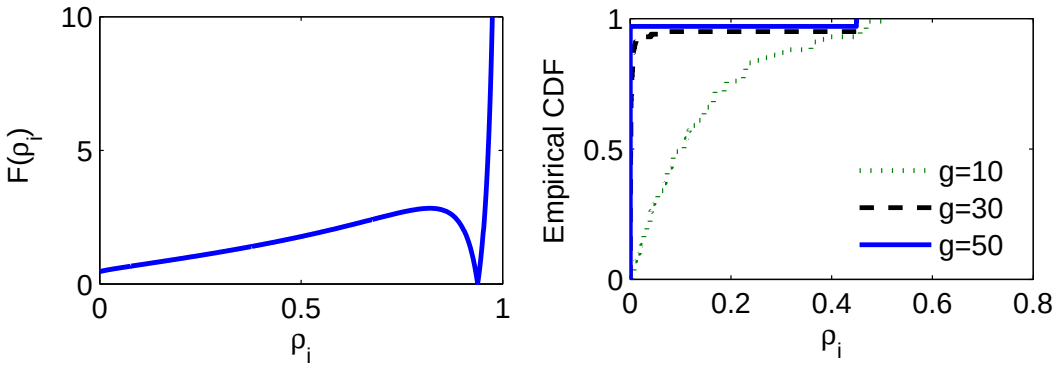

Figure 4: $F(\rho_i)$ simulated for different ρ_i and empirical distribution of $F(\rho_i)$ for different g

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