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Do systemic innovation intermediaries broaden horizons? *A proximity perspective on R&D partnership formation*

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ABSTRACT
As systemic innovation intermediaries (SII) orchestrate interactions between innovative actors, they might alleviate the constraints of proximity effects on R&D partnership formation. We test this for existing and new R&D projects established under the Dutch Topconsortia for Knowledge and Innovation. Regression results show that partnerships between firms belonging to the same SII are less sensitive to cognitive proximity, suggesting that the intermediaries facilitate uncommon distant collaboration. At the same time, we find that SII may strengthen social proximity among partners. The influence of organisational proximity seems independent of SII, while geographic proximity loses relevance after the introduction of the intermediaries. SII thus seem to create bridges between distant firms that otherwise may not have collaborated together, while also enhancing the risk of excessive in-group thinking. We conclude with research and policy implications.

Abbreviation: Research and development (R&D)

KEYWORDS
Systemic innovation intermediary; R&D collaboration; proximity; innovation policy

JEL CLASSIFICATIONS
O31; O32; O38

1. Introduction

For economies to stay adaptive, it is essential to continuously accumulate new knowledge and capabilities (Asheim, Boschma, and Cooke 2011; Boschma et al. 2017). Recombinant growth is known to follow from firms' entrepreneurial experimentation with complementary pieces of knowledge (Weitzman 1998; Cassiman and Veugelers 2006). Especially when aiming to diversify into genuinely novel directions, the challenge is to establish exchanges between relatively unrelated knowledge bases (Frenken, Van Oort, and Verburg 2007; Castaldi, Frenken, and Los 2015). According to Boschma's (2005) proximity theory, however, firms are generally inclined to collaborate with similar and nearby partners; it is a common tendency for them to source knowledge they can easily absorb (Nooteboom 2000), in particular from partners that are part of their own environment (Gulati 1995; Rycroft and Kash 2004; Boschma 2005; Balland 2012). Organisational and strategy studies have shown how factors like geographic, social and institutional proximity influence search and recombination processes resulting in innovation (Savino, Messeni Petruzzelli, and Albino 2017). Due to proximity

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constraints at the firm-level, also economies as a whole are often limited to branching into related activities (Boschma and Iammarino 2009; Boschma 2011). Indeed, escaping the competency trap or even lock-in that lurks constitutes a clear basis for policy intervention (Boschma et al. 2017; Balland et al. 2018).

One particular way in which governments may aim to address myopic knowledge sourcing is by actively coordinating collaborations between private and public organisations engaged in R&D (Dhanaraj and Parkhe 2006; Hurmelinna-Laukkanen et al. 2012). An important role in this respect is ascribed to innovation intermediaries; agents that operate as brokers in innovation processes involving interactions between multiple parties (Howells 2006; Russo et al., 2019). Several qualitative studies have touched upon the impact of innovation intermediaries on firm-level value creation or R&D collaboration, for instance in domains like ICT (Larty, Jack, and Lockett 2017) or agriculture (Kilelu et al. 2011). Besides intermediaries connecting and supporting individual actors in their own network, there are intermediaries that act at a high systemic level, e.g. innovation systems in regions or countries (Klerkx and Leeuwis 2009). Such systemic intermediaries typically deal with complex networks and problems and are important in facilitating and coordinating efforts for long-term change (van Lente et al. 2003; Kilelu et al. 2011). Functions of the systemic intermediaries include strategy development, network and trust building, knowledge brokerage, or organising discourse (Howells 2006).

From the perspective of spurring uncommon knowledge recombination, a particularly relevant but relatively neglected sub-set of systemic intermediaries is found in the type that is concerned with orchestrating R&D partnerships in line with collective research agendas. Examples include research councils, research and technology organisations, national strategy boards and innovation coordination groups actively programming R&D activities (Knockaert and Spithoven 2014; De Silva, Howells, and Meyer 2018). By drawing on their network building and brokerage capacities (Howells 2006; Abbate, Coppolino, and Schiavone 2013), such 'systemic innovation intermediaries' (SII) are well-positioned to reconfigure collaborative knowledge development. However, since systematic large-scale investigations on the effects of SII are missing, there is no comprehensive examination of their actual influence on firms' partner choices. As a result, it remains unknown whether SII reinforce existing R&D collaboration tendencies, or rather entice firms to 'broaden their horizon' with regards to new and previously unrelated partners.

This paper aims to explore how the presence of SII, characterised by guiding system-level R&D efforts, relates to changes in R&D collaboration patterns. Specifically, we assess whether SII affect the chance that firms form a new R&D partnership, and to what extent SII can alleviate the influence of different proximity dimensions in this respect.

Our empirical analysis of SII considers the 12 Dutch Topconsortia for Knowledge and Innovation (TKI). In 2013, the Dutch government implemented these industry-specific entities to unite research-intensive actors and to strengthen the national R&D network within and across industries. Using a logistic regression framework we compare the effects of different proximity dimensions (geographical, cognitive, social and organisational proximity) on the formation of ties before and after the implementation of the TKI in the period 2013–2016. To further discern TKI effects we differentiate between the formation of new intra-industry and new cross-industry ties.

Our study contributes to current debates on policy interventions for transforming R&D networks and ultimately driving unrelated diversification (Boschma et al. 2017; Balland et al. 2018). We position SII as a means for policymakers to overcome the constraints of proximity and boost knowledge exchange beyond the ordinary. Quantitative research on the orchestrating role of intermediaries is scarce. By analysing R&D partnership formation subjected to industry-specific SII, we provide first empirical evidence with regards to the effectiveness of these intermediaries in accelerating new inter-firm knowledge linkages.

The paper is organised as follows. After introducing the concept of SII, we propose hypotheses regarding their influence on inter-firm R&D collaboration (section 2). Section 3 describes our empirical setting as well as the data and methods. We present our results in section 4. Section 5 concludes.

2. Theory and hypotheses development

2.1. Systemic innovation intermediaries (SII)

The literature on *innovation intermediaries* has been quite dispersed, as it emerged from research fields concerned with technology transfer, R&D, innovation and systems of innovation (Howells 2006; Kivimaa 2014). According to Howells (2006) innovation intermediaries 'act as an agent or broker in any aspect of the innovation process between two or more parties' (Howells 2006, p. 720). Originally studies on intermediaries focused primarily on firms as central 'hubs' who shape and manage their own (R&D) network of partners, as a side-activity to their core business (Doz, Olk, and Ring 2000; Dhanaraj and Parkhe 2006; Gassmann, Daiber, and Enkel 2011). In more recent contributions the term innovation intermediary is often attributed to gatekeeper entities that exclusively focus on enabling other organisations to innovate, rather than being involved in the development and implementation of innovations themselves (Winch and Courtney 2007; Batterink et al. 2010; Kilelu et al. 2011; Abbate, Coppolino, and Schiavone 2013; De Silva, Howells, and Meyer 2018). Such activities might be performed by for instance technology-transfer offices, university incubators and collaborative research centres (Villani, Rasmussen, and Grimaldi 2017).

The label *systemic intermediary* has been posed to refer to those entities that operate at a high systemic level, going beyond the networks around a particular actor (Klerkx and Leeuwis 2009). Systemic can refer to sectors or regions, but has also been associated with innovation systems and multi-level perspective concepts (van Lente et al. 2003; Kivimaa et al. 2019). Many intermediaries are organised in the form of non-profit or public organisations (Kilelu et al. 2011; van Lente et al. 2011; Hannon, Skea, and Rhodes 2014), often of a government-affiliated nature (Kivimaa 2014). To facilitate interaction between parties, systemic intermediaries perform a range of functions. These include network building and sustainment; knowledge brokerage; trust building amongst actors in the network; demand articulation and strategy development; process management of long-term and/or complex projects; organising discourse, alignment and consensus; institutional support; creating conditions for learning by doing, using, interacting and searching; provision of tailor-made (strategic) information; and R&D funding (van Lente et al. 2003; Howells 2006; Dalziel 2010; Kilelu et al. 2011). Since systemic intermediaries are

sometimes active within a specific industry, industry promotion may be another function they perform (van Lente et al. 2003; Winch and Courtney 2007; Dalziel 2010).

So far, the literature on systemic intermediaries has mostly been concerned with exploring what roles they might play in socio-economic transformations, ranging from creating niches for new, often disruptive, technologies, over mobilising finance and the involvement of users to accelerate processes of technological or institutional change (Kivimaa et al. 2019). How systemic intermediaries relate to innovation intermediaries, however, has remained rather neglected. One possible configuration is that systemic intermediaries articulate widely backed innovation or transition agendas, while entities like innovation intermediaries are involved in transferring and exploiting the knowledge created in the execution of these agendas. Another possibility is that systemic intermediaries themselves are tasked to coordinate the collective knowledge development required for moving the desired innovations forward. An example of the latter can be found in Kivimaa's (2014) case study on Motiva, a Finnish publicly owned systemic intermediary involved in implementing energy efficiency policy. Rather than engaging in strategy development, it deploys activities focused at network creation, gatekeeping, knowledge dissemination and the development of actual experimental projects. Systemic intermediaries like these perform a knowledge brokerage function in the sense of a more classical innovation intermediary but linked to implementing directed research activities of different actors.

Recognising the lack of attention for specifically this type of intermediary, we regard '*systemic innovation intermediaries*' (SII) as organisations involved in orchestrating system-level collective R&D and innovation activities. *System-level* denotes that the intermediaries arrange their activities not around a specific actor (e.g. a research institute), but around the shared vision of a broader set of actors. In the context of *R&D and innovation*, this is likely to have the shape of a collective agenda, outlining research roadmaps feeding into the development of a particular innovation path. Finally, *orchestrating* consists of brokerage oriented towards knowledge creation and exchange in the context of such an agenda. Amongst organisations typically acting as a systemic innovation intermediary, we find research foundations or research and technology organisations actively involving public and private actors in the collaborative execution of a thematic research program. By creating and shaping R&D networks, SII might contribute to generating innovation and knowledge spillovers that can boost economic growth (Cohen 2006) as well as the socio-technical change required for transitions to succeed (Kivimaa et al. 2019). The particular question we pose is to what extent this orchestrating ability results in R&D collaborations deviating from ordinary patterns.

2.2. Proximities as a determinant of R&D partnership formation

Firms normally choose to collaborate based on the expected utility of a partnership. This utility can be derived from the direct partner by sharing of resources and risks (Williamson 1981), access to a partner's unique resources, including indirect partners and a knowledge network (Wernerfelt 1984; Schilling and Phelps 2007), or the opportunity to engage in organisational learning and joint knowledge production (Powell, Koput, and Smith-Doerr 1996; Nooteboom 2000).

There are several strands of literature discussing proximity in different dimensions, as factors that facilitates the effective exchange of knowledge between agents engaging in, for instance, alliances or collaboration networks (Carrincazeaux, Lung, and Vicente 2008). Contributions stemming from organisational and strategy studies have pointed at proximity types relevant for knowledge sharing, knowledge transfer and technology acquisition (Knoben and Oerlemans 2006). By building on this literature, scholars in the innovation management field analyse how proximities mediate processes of searching and recombining knowledge elements (Savino, Messeni Petruzzelli, and Albino 2017). Besides establishing that higher proximities often facilitate the ease of knowledge exchange, innovation management scholars have also assessed and contextualised the influence of, for instance, geographical or organisational proximity, on dependent variables like firm performance, innovation performance, or alliance performance (Miller, Fern, and Cardinal 2007; Capaldo and Messeni Petruzzelli 2015). As Capaldo and Messeni Petruzzelli (2014) show for knowledge-creating R&D alliances, the effects of orthogonal dimensions like geographic and organisational proximity may be contingent upon each other.

The concept of proximity, in particular in relation to interactive learning and innovation, has also had a major influence on the development of the evolutionary economic geography field. In a seminal contribution on proximity and innovation, Boschma (2005) proposed a proximity framework consisting of five dimensions. Part of his critical assessment was the effort to devise mutually exclusive dimensions, for instance by separating cognitive proximity from organisational proximity. Inherent features of the framework are also that the learning-inducing effects of proximities do not need to be linear, and that a lacking proximity on one dimension may be compensated by higher proximity on the other dimensions. Given its strength in analytically differentiating the proximity dimensions, Boschma's (2005) five-dimensional proximity framework dominated much of the ongoing research on the coordination of knowledge recombination activities (Balland, Boschma, and Frenken 2015; Villani, Rasmussen, and Grimaldi 2017).

In this framework, *geographical proximity* pertains to the spatial distance between two firms; by facilitating face-to-face interaction, lower distance generally facilitates learning (Paier and Scherngell 2011). *Cognitive proximity* denotes to what extent firms are similar in their perception, interpretation and understanding of phenomena. When firms possess a knowledge base that is alike, it will be easier to absorb each other's knowledge (Cohen and Levinthal 1990; Nooteboom 2000). Indeed, there is ample evidence showing that firms are more likely to collaborate when cognitive proximity is higher (Autant-Bernard et al. 2007; Cantner and Meder 2007). In order to assess the benefits of collaboration, also the firm's network position is regarded as a determinant of cooperation (Bala and Goyal 2000). *Social proximity* covers the degree to which firms have common relationships. By being a foundation for trust building, sharing more partners again increases the likelihood that collaboration can emerge (Boschma 2005). *Organizational proximity* refers to the rate of autonomy and control that can be exerted in organisational arrangements, which has to do with hierarchy in the governance structure (Boschma 2005). Torre and Rallet (2005) define organisational proximity as the ability of organisations to make their members interact, which is facilitated by sharing a 'same system of representations, or set of beliefs'. Firms that are more similar

in their implicit or explicit routines are often found to be more inclined to collaborate (Knoben and Oerlemans 2006). Finally, *Institutional proximity* can be defined as the extent to which 'actors [share] the same institutional rules of the game, as well as a set of cultural habits and values' (Boschma 2005). Often this is operationalised as agents being in the same country (Ponds, Van Oort, and Frenken 2007).

Briefly stated, collaboration is more likely when firms are located closer to each other (geographical proximity), share similar knowledge (cognitive proximity), engage in the same communities (social proximity), have a similar degree of autonomy in coordinating knowledge exchange (organisational proximity), or act according to the same norms and rules (institutional proximity). And while the various dimensions can substitute and complement each other, generally each of them individually is believed to have a positive impact on the ease of interactive learning (Balland, Boschma, and Frenken 2015). On this basis we can derive the baseline hypotheses for this study[1]

Baseline hypotheses 1a-1d

Firms are more likely to collaborate in R&D when they have a higher:

(a) geographical proximity
(b) cognitive proximity
(c) social proximity
(d) organizational proximity

Before moving to the influence of SII, it is important to stress that across all of the proximity literatures there are indications that an increased likelihood of collaboration does not necessarily yield a better outcome (for the firms involved, or the economy they are part of). Collaborations at high levels of proximity are associated with a risk of lock-in (Boschma 2005). In such conditions interaction might be easier, but less novel in terms of the innovation it generates. For instance, collaboration strongly depending on high geographical proximity is harmful when firms overlook promising learning opportunities outside their region (Capaldo and Messeni Petruzzelli 2015). Similarly, a high degree of social proximity may lead firms to engage in excessive in-group thinking. The overlapping knowledge base characterising high cognitive proximity allows firms to understand each other but also limits the potential for novel knowledge recombination. Too much organisational proximity, finally, hampers feedback mechanisms as well as the flexibility required for altering exchange relations. Collaborating only at small distances may thus result in the type of inward-looking behaviour impeding innovative experimentation. For policymakers, this drawback implies a need for mechanisms allowing firms to open up to new ideas and complementary pieces of knowledge (Asheim, Boschma, and Cooke 2011; Boschma et al. 2017). Intermediaries may be one way to lower the barriers for novel knowledge recombination to take place.

[1]Our empirical analysis concerns R&D collaboration within the Netherlands, considered as one coherent institutional framework. We therefore do not derive a hypothesis and empirically investigate the effects of institutional proximity.

2.3. The influence of SII on R&D partnership formation

The focus of our study is how SII moderate the influence of the proximities. Acting as middleperson between various parties, systemic intermediaries are acknowledged to transform regular patterns of interaction (van Lente et al. 2003). Network building and brokerage are considered to be two of their most prominent activities for spurring collaborative innovation (van Lente et al. 2011; Hannon, Skea, and Rhodes 2014). The demand for guidance and clarity grows as R&D and product development increasingly take place in multi-actor knowledge networks. Drawing upon the literature on open innovation and R&D alliances, we recognise possibilities for SII to fulfil part of the screening process required for firms to identify unknown but relevant partnership possibilities. Searching for promising ideas and partners is observed to be costly, especially when looking beyond the readily accessible networks and knowledge domains (Laursen and Salter 2006; Capaldo and Messeni Petruzzelli 2014). Rather than requiring firms to bear these costs individually, intermediaries operating at a systemic level are in the position to efficiently coordinate the exploration of fruitful knowledge-creating partnerships. SII may deploy R&D orchestrating activities to support innovative actors, for instance by collecting and sharing information on who in the network possesses or needs a certain type of knowledge or by establishing joint events or a joint agenda. As such, intermediaries can establish communication between parties, making them aware of their matching goals (Backhaus 2010).

There is only a limited amount of empirical evidence that can strengthen our conjectures on the role of SII as horizon-broadening collaboration facilitators. A single case-study on a for-profit intermediary suggests that they are indeed able to bridge *cognitive distance* between agents (Mahnke, Wareham, and Bjorn-Andersen 2008). According to Abbate, Coppolino, and Schiavone (2013), intermediaries promote knowledge sharing amongst sets of actors that would normally not interact or collaborate due to *network* or geographic barriers. By creating a platform for discourse, alignment and consensus (van Lente et al. 2003), intermediaries might even support partnerships between firms operating in distinct types of *organizational* contexts. The potential to bridge organisational and social distance also appears from a qualitative case study by Kivimaa (2014), finding that stakeholders assign high value to the role of the intermediaries for new network formation. Recently, Villani, Rasmussen, and Grimaldi (2017) have shown how intermediary organisations can in fact differ in the specific proximity dimensions they target.

Together, the proximity perspective and case-based insights let us expect that SII help to overcome the constraints of various distances. Due to SII's potential to support low proximity collaboration, pairs of firms subjected to the same intermediary might be less sensitive to the proximity effects on partnership formation. This leads us to our 'SII hypotheses':

SII hypotheses 2a-2d

The influence of proximities (a-d) on R&D collaboration is less pronounced for firms subjected to the same SII than for firms subjected to different SII.

3. Data and methodology

3.1. Case description

The Dutch government implemented its latest national research and innovation strategy in 2012. The so-called 'Topsector approach' focuses on nine specific knowledge domains combining scientific and economic excellence (Janssen 2019). The objective of sustaining this success is pursued via the collective development of 'research and innovation agendas'. Resulting from extensive deliberation between science, industry and government representatives within Topsectors, these agenda's do not just consider technology development, but also aspects related to the actual use and diffusion of the resulting solutions. One of the policies designed to spur the desired innovation trajectories is the support for public-private R&D partnerships fitting the pathways laid out in the research and innovation agendas.

A pivotal role in the Topsector approach is played by the 12 government-affiliated Topconsortia for Knowledge and Innovation (TKI) established in 2013. They perform various activities related to implementing the research agendas, including: shared goal-setting and demand articulation, by facilitating bottom-up roadmap writing (involving again industry and science representatives); network building activities, e.g. by organising professional events; industry lobbying; and R&D funding; directly as well as by spreading the word about research calls. The nationally oriented TKI operate in between private organisations, such as small and medium-sized enterprises (SMEs) and large firms, and public organisations, such as public research organisations (PROs) and universities. TKI also play a role in connecting firms with each other, be it within the same industry or between industries (depending on the scope of the research agendas they are implementing).

Considering the combination and scope of the functions they perform in the orchestrating of system-level R&D activities, TKI can be regarded as SII. Whereas each TKI puts its own accents, all of them aim to spur collaborative knowledge development by involving parties in R&D projects fitting their research agenda. Typically, these projects last between 3 and 4 years. Due to the collaborative nature, most projects are in the precompetitive rather than a competitive stage of R&D. From the outset, however, there are no general requirements in terms of, e.g., project originality or the knowledge, skills or location of firms involved in the project-based partnerships (except that most TKI undertook some efforts to ensure also SME involvement, albeit usually only as a minor side objective). Therefore, the TKI make for a suitable case to study their relation with overcoming (or reinforcing) proximity effects.

3.2. Data description

The TKI steer and co-fund collaborative R&D projects by using subsidies (allowances) based on private financial contributions to existing public-private research projects. The funding administration we obtained contains information about the composition of all newly formed projects after the implementation of the TKI (in 2014–2016) and of projects already running before the activities of the TKI (in 2013). Observing R&D projects at two different points in time is essential for assessing the influence of TKI on new partnership formation. The pre-existing projects are usually administered to a TKI

by a research institute; an aspect which is important for the study at hand as it reveals to which TKI a firm is subjected (firms involved in multiple projects might be subjected to one or more TKI). From an intermediary perspective, bringing together actors that already knew each other is not as relevant as stimulating new connections. Interviews with R&D managers and TKI staff members reveal that the TKI activities played indeed a role in establishing new collaborations (Dialogic 2016).

The actor set we study contains all organisations that participated in at least one R&D project before the TKI existed. Out of the 674 unique Dutch participants in these projects, 589 are firms. In 2013, there was a total of 381 ongoing projects involving at least two firms. Over the three subsequent years, these participants became involved in 531 newly initiated projects.

To study the influence of TKI on collaboration formation, we combine the actor set with the project information to construct two different networks of R&D project collaborations. The initial network (t_0) including all 674 actors covers the pre-existing projects in 2013 (before the implementation of the TKI); the comparison network (t_1) is constructed using the same actor set as the t_0 network (i.e. new actors are not taken into account) to study whether *new ties* are formed between those actors not linked in t_0. For both networks, we consider two actors connected by a tie when they participate in at least one project together. This yields a non-weighted, one-mode network of R&D project collaboration.

3.3. Empirical model specification and variable construction

We are interested in the question of whether different forms of proximity influence the probability of R&D collaboration between two firms and whether, in turn, the TKI did affect the collaboration choice of these firms. As common in the literature on R&D collaboration (e.g. Autant-Bernard et al. 2007; Paier and Scherngell 2011), we consider a latent variable model observed as a binary logit model (Long and Freese 2001) to estimate the probability of collaboration between two firms. Accordingly, the dependent variable is observed as a binary variable, taking the value of one if a tie is formed between any pair of firms in our actor set, and zero otherwise. Note that we consider only firms for the construction of our dependent variable. A total of 589 firms implies 173,166 potential inter-firm ties. We find 1,968 actual ties in the t_0 network and 2,213 in the t_1 network, as 245 new ties were created at t_1.

To study the influence of the TKI as systemic intermediaries, we run two types of binary logit models.[2] The first one, referred to 'baseline regressions' serves to inspect the role of the proximities and the TKI independently from each other. Looking at the situation *before* and *after* the TKI came into play, we look at the variables' influence on the formation of ties at t_0 and new ties at t_1. The latter only includes genuinely novel ties: t_0-ties renewed at t_1 are excluded from the model. The second set of regressions ('SII regressions') is used to test our hypotheses on how being subjected or not being subjected to the same TKI affects the influence of proximity dimensions on new tie formation at t_1. Simply entering interaction terms into a non-linear model may cause ambiguous results (Ai and Norton, 2003). Instead, we split our sample into two groups: one group including

[2]Inspection of alternative logit models suggest that our results are not biased due to rare events data structure.

ties potentially formed by pairs of firms who were subject to the same TKI at t_0; and one group covering the ties for firms who were subjected only to different TKI. On this basis, we are able to compare the coefficients for all independent variables. For all regressions, maximum likelihood estimation (MLE) is used to estimate the coefficients.[3]

The independent variables reflecting the proximity dimensions are observed as follows:

Geographical proximity (Geo) is measured as the inverse geographical distance in kilometres (geodesic distance) between two firms' locations according to their addresses registered in our database.

Cognitive proximity (Cog) between two firms is approximated by a revealed *skill relatedness* measure (Neffke, Otto, and Weyh 2016). This concept refers to similarities between the skills and knowledge required by workers in different industries. Their relatedness is determined based on labour mobility between each pair of 4-digit NACE-codes in The Netherlands. The data contain the number of labour market transfers in 2009 and 2010 from each 4-digit NACE code to the other. We calculate skill relatedness (SR) by following the method by Neffke, Otto, and Weyh (2016). Assuming that one firm can reach out to another one if cognitive proximity is high enough, we use the maximum of the directed normalised skill relatedness between their industries as an undirected measure. Typically, patent or publication data are used to create proxies for cognitive proximity (Messeni Petruzzelli, Albino, and Carbonara 2009), while using industry-based skill relatedness as a determinant for inter-firm R&D collaboration is less common in the literature. Our measure has the advantage that it is available for all firms and not dependent on a firm's ability to patent or publish.

Social proximity (Soc) is approximated by two measures that represent the extent to which two firms are able to 'discover' each other as possible new partners. This knowledge about potential partners and the creation of required trust often is mediated by previous partners. Hence, we measure social proximity by the number of direct partners two firms share in t_0 (*shared partners*). The second measure is calculated at the network level measured as the inverse geodesic distance (*network proximity*) between any pair of firms in the t_0-network. Both social proximity measures are calculated on the basis of the full network (including private and public organisations) in t_0.

Organisational proximity (Org) between firms can be measured in many different ways, as this proximity dimension is known to suffer from conceptual ambiguity (Knoben and Oerlemans 2006). Interpreting it as the structural equivalence of actors that facilitates mutual understanding (Rice and Aydin 1991), organisational proximity is approximated here by following Boschma's (2005) claim that it should capture similarity in organisational arrangement. Firstly, as it is recognised that SME (<250 employees) and large firms (≥250) differ in their knowledge management and creation strategies (McAdam and Reid 2001), we determine whether two firms share an organisational type (*firm types;* SME or Large firm). An additional ad-hoc measure fitting our particular context states whether firms share their research orientation (*research types*), which can be fundamental or applied research as determined on the basis of their projects at t_0. In the variable construction, we take into account that firms typically are more oriented towards applied research. A firm qualifies as 'fundamental' if it has

[3]As a robustness check, we also calculated Average Marginal Effects (Choirat et al. 2017). The results show that there are only minor differences in the estimated coefficients and significances between the methods.

been able to engage, at all, in a t_0-project involving a fundamental research institute. Otherwise, we consider that firm as being oriented towards applied research. At the tie-level, both organisational proximity measures are operationalised as dummy variables according to the three possible categories. For both measures, firm types as well as research types, ties between different types is used as reference category in our model (i.e. firm types '*SME with large firm*'; research types '*applied research firm with fundamental research firm*').

Lastly, to assess the influence of the SII we construct a binary variable that indicates whether two firms are subjected to the same TKI (*same TKI*). It takes the value one if both firms have participated in at least one project registered under the same TKI at t_0, and zero otherwise.

To account for alternative factors that explain the likelihood to form a new tie, several control variables are included: Firstly, the number of R&D projects the firms participated in at t_0, calculated as the mean number of projects of the two firms (*mean projects)*, controls for the firms' R&D potential. Secondly, the number of partners of each firm at t_0 is taken into account (*mean partners)*, calculated as the mean number of unique partners of the two firms. Lastly, to control for sectoral differences, a dummy is included that indicates whether two firms are in the same sector (based on their 2-digit NACE code), taking the value of one for the same classification, and 0 otherwise (*dummy same industry*). An overview of all the variables and corresponding descriptive statistics are given in Table A1 and Table A2 in the Appendix, followed by a series of correlation Tables A3 – A6. None of the proximity measures or control variables correlates substantially with the variable of being subjected to the same TKI. Table A7 provides some characteristics of the corresponding R&D networks.

Table 1. Results of the logit regression model for tie formation at t_0 and t_1.

	Model 1 (t_0)	Model 2 (t_1)	Model 3 (t_1)	Model 4 (t_1)
Geographical proximity (Geo)	0.663 ***	0.308	0.298 *	0.282 *
	(0.051)	(0.141) *	(0.140)	(0.138)
Skill relatedness (Cog)	0.813 ***	0.629 ***	0.473 ***	0.348 **
	(0.050)	(0.127)	(0.125)	(0.124)
Network proximity (Soc)	-	-	0.259 **	0.032
			(0.095)	(0.099)
Shared partners (Soc)	-	-	0.435 ***	0.273 ***
			(0.054)	(0.058)
Both SME (Org)	−0.023	−1.511 ***	−1.245 ***	−1.280 ***
	(0.051)	(0.196)	(0.202)	(0.203)
Both large firms (Org)	1.109 ***	2.074 ***	1.661 ***	1.681 ***
	(0.073)	(0.140)	(0.147)	(0.147)
Both applied research (Org)	-	-	−0.201	−0.244
			(0.158)	(0.159)
Both fundamental research (Org)	-	-	0.475	0.495 **
			(0.185) *	(0.184)
Same TKI	-	-	-	1362 ***
				(0.163)
Mean projects	-	-	0.064	0.065 **
			(0.020)	(0.020)
Same industry	0.846 ***	−0.169	−0.206 **	−0.263
	(0.065)	(0.261)	(0.265)	(0.264)
Constant	−4.24 ***	−6.198 ***	−5.721 ***	−6.683 ***
	(0.056)	(0.153)	(0.339)	(0.369)
AIC	20,244	3,261	3,083	3,018
McFadden's pseudo-R2	0.061	0.122	0.172	0.191

4. Results

4.1. Baseline regressions

To assess the importance of the proximities and the TKI in explaining the formation of R&D collaboration ties, Table 1 shows the estimation coefficients of the baseline regressions. The first block (Model 1) shows the results for ties formed at t_0. To inspect how the influence of proximities change after the implementation of the TKI, the second block shows the results if new ties formed at t_1 are considered. For comparison reasons, model 2 only includes the independent variables that were already available for model 1. Model 3 extends this by including the independent variables constructed with t_0-data, while model 4 additionally considers whether firms participated in the same TKI at t_0.

At t_0, geographical proximity has a strong positive relation with tie formation. This relation is weaker and less significant in the period 2014–2016 (at t_1). For cognitive proximity (skill relatedness), the positive relation remains strong over the two periods. Interestingly, both variables for social proximity show a significant positive coefficient in Model 3, but the network proximity variable loses significance when we control for the same TKI (Model 4). For firm types, we observe consistent patterns, showing that especially large firms have a higher probability of seeking each other out compared to collaborating with firms of different types. Smaller firms are less likely to form a tie with each other than with a large firm (the reference category). Also, firms engaged in t_0-projects involving fundamental research institutes have a slightly higher tendency to work with each other than with firms that only worked with applied research institutes. Given the consistency of results across the different models, baseline **hypotheses 1a, 1b and 1c** can be confirmed. For **hypothesis 1d** we find that organisational proximity is only a positive predictor for new tie formation between large firms.

As for the intermediaries themselves: being subjected to the same TKI clearly has a highly significant relation with the probability of a new tie being formed.

4.2. SII regressions

Now we turn our attention to the split-sample analyses based on pre-determined subgroups. We separately estimate the effects of the full range of predictors on ties between firms who were subjected to the same industry-specific TKI at t_0, ('Same-TKI ties'; Model 5), and on 'Cross-TKI ties', i.e. the remaining ties (Model 6). The results of the logistic regression on the subgroups are given in Table 2.

The results of Model 5 and Model 6 indicate that in none of the two groups *geographical proximity* is a significant predictor. Contrary to the findings for the baseline models, there is no indication that geography still matters in the TKI-era. The results suggest that the presence of TKI generally reduces the influence of geographical proximity. Since we do not observe any significant differences between the Same-TKI and Cross-TKI groups, we cannot confirm Hypothesis 2a.

Regarding cognitive proximity, *skill relatedness* has a positive and significant effect on new tie formation for the Cross-TKI subgroup. When firms are subjected to a different TKI, a higher cognitive proximity still increases the chance they will start collaborating (see Model 6). In case firms are subjected to the same TKI (Model 5), however, cognitive proximity no longer matters. This is in line with the expectation that

Table 2. Results of the logit regression model (sample split for Same-TKI and Cross-TKI tie formation at t_1).

	Model 5 (same TKI)	Model 6 (cross-TKI)
Geographical proximity (Geo)	0.193	0.337
	(0.193)	(0.196)
Skill relatedness (Cog)	0.260	0.468 **
	(0.180)	(0.170)
Network proximity (Soc)	1.033 ***	−0.255 *
	(0.308)	(0.128)
Shared partners (Soc)	0.281 ***	0.190
	(0.065)	(0.195)
Both SME (Org)	−1.022 ***	−1.419 ***
	(0.289)	(0.293)
Both large firms (Org)	1.473 ***	1.845 ***
	(0.211)	(0.203)
Both applied research (Org)	−0.693 **	0.009
	(0.240)	(0.222)
Both fundamental research (Org)	0.239	0.805 **
	(0.251)	(0.261)
Mean projects	−0.008	0.156 ***
	(0.028)	(0.028)
Same industry	−0.246	−0.326
	(0.333)	(0.439)
Constant	−2.600 ***	−8.095 ***
	(0.728)	(0.516)
AIC	1,247.9	1,743.5
McFadden's pseudo-R2	0.175	0.143

intermediaries (in this case acting upon certain industries) help firms overcome cognitive distance in forming new partnerships. **Hypothesis 2b** can be confirmed.

Also for *network proximity*, we see an interesting result for Cross-TKI. In Model 6, network proximity has a negative and significant effect on new tie formation, implying that firms at a larger distance in the initial collaboration network are more likely to form a new partnership. In Model 5 for Same-TKI, on the other hand, network proximity has a strong significant and positive relation. Within the TKI industries, there is a tendency for firms to form new ties with actors that are relatively close to them. A similar pattern can be observed from *shared partners*, which has a positive significant effect for Same-TKI. Firms subjected to the same TKI tend to form new ties with their partners' partners: 'triadic closure' occurs more likely within the same TKI. Therefore, **hypothesis 2c** is rejected.

Interestingly, concerning organisational proximity we observe in both models a similar pattern for the *firm types* variables: negative and significant for SME-SME pairs compared to SME-Large pairs; and positive and significant for Large-Large pairs as compared to SME-Large. Recall from the baseline models that at t_0, there was only a positive significant effect for Large-Large firm pairs. The negative significant effect appearing at t_1 for SME-SME pairs now turns out to hold for both subgroups; the likelihood of partnership formation between a SME and large firm is consistently larger for both TKI groups than a partnership between any two SME firms. With respect to the *research types* variables, we find that in subgroup Same-TKI there is a negative significant effect for firm pairs oriented only towards applied research. Apparently, they are less likely to form a new partnership than pairs involving at least one firm that engaged in projects with a fundamental research institute. In subgroup Cross-TKI, two firms oriented towards fundamental research are more likely to form new ties than

a fundamental and an applied research firm. For pairs of applied research firms, there is no significant effect. Since the TKI reduce the likelihood of collaboration between applied research firms without increasing the likelihood of fundamental research partnerships, we are unable to confirm **hypothesis 2d.**

Lastly, the control variable *mean projects* has a positive and significant effect only in subgroup Cross-TKI. Partnerships beyond the scope of the individual TKI are most likely to emerge between firms having a high R&D collaboration potential in the first place. The variable *dummy same industry* is not significant in Table 2.

5. Conclusion

5.1. Discussion

Despite the acclaimed potential of innovation intermediaries to orchestrate interactions, still very little is known about the overall effects they have on R&D collaboration patterns (Abbate, Coppolino, and Schiavone 2013; Dalziel 2010). This study provides first quantitative insights into the role of systemic innovation intermediaries (involved in orchestrating system-level innovation efforts) in R&D partnership formation. Rather than alleviating all the investigated proximity effects, we found for the case of Dutch TKI that they seem to rebalance the respective importance of various proximity dimensions.

First, perhaps our most important finding is that cognitive proximity loses its influence on partnership formation if firms are subjected to the same TKI. As is often the case for systemic intermediaries (van Lente et al. 2003; Winch and Courtney 2007), the 12 TKI in our study are industry-specific. While there was still a considerable spread of the skill relatedness variable within TKI, we do not observe that the effect of cognitive proximity is reinforced by the intermediaries' network building activities. Instead, it appears that the intermediaries facilitate collaboration over more cognitive distance than commonly found. We stress that this particularly holds for partnerships *within* the intermediaries' industry-specific scope (as embodied in its research agenda, topics of network events, for instance). For partnerships between firms subjected to different TKI, skill relatedness remains a strong predictor for whether a tie will really emerge or not. This suggests that the industry-specific intermediaries, despite occasional ambitions to create linkages with firms from other TKI, so far have mostly constructed links between sub-networks falling into the set of knowledge domains they span themselves.

That having said, we also noticed that the influence of geographical proximity decreased after the implementation of the TKI. Firms originally had a preference for collaborating with local partners, whereas under the TKI they also seek for geographically more distant partners. Given that TKI have been implemented at the national scale, we might have encountered a sign that intermediaries at the national level are to a certain extent able to override local clusters.

Then again, social proximity is an important influence specifically within firms subjected to the same TKI, suggesting that the observed broadening of horizons, in fact, follows existing network structures. Of particular relevance is that in our specific case, firms themselves had a say in the research agendas that were developed together with academia, public research organisations and the government (Dialogic 2016). The top-down selected TKI are essentially acting as implementers of bottom-up policy, steering research towards the avenues supported

by the firms they represent (Backhaus 2010). Our finding that the core communities within the TKI domains have now become even more tight-knit implies a possibility, or rather risk, that selected groups of actors consolidate their existing social structure by utilising policy measures they partially shaped (Fromhold-Eisebith and Eisebith 2005). Whether these partnership formation tendencies within TKI puts those that are not initially part of the relevant research community at a distinct disadvantage, is a question that can be answered in follow-up research also including firms who entered a network.

As for organisational proximity, the findings regarding collaboration between SME and large firms are not supporting the hypothesised positive effect of having a similar organisational structure. Here one should note that most of the intermediaries in this study had the side objective of involving more SME in public-private research. Although receiving only minor attention, it is reassuring that the SME-Large collaboration probability is especially increased amongst firms subjected to the same TKI. The same holds for collaboration between firms with a different research orientation. Since the TKI policy is specifically aimed at involving industry more in public-private research, it is not surprising that within TKI there is a lower tendency for firms oriented towards fundamental research to mainly work with each other. In sum, besides the possible effects of industry-specific SII, it seems that the associated policy objectives are also of key importance for altering patterns in R&D partnership formation.

5.2. Theoretical implications

The current study advances the innovation intermediary literature both by deepening as well as extending it. A first contribution consists of acknowledging the existence and abilities of research-oriented innovation intermediaries active at a system-level, so-called systemic innovation intermediaries (SII). While there is an extensive body of literature on intermediaries operating in local networks or a knowledge transfer setting (Russo et al., 2019), few authors have recognised the role intermediaries can play in orchestrating R&D within or even beyond broad knowledge domains and industries (Klerkx and Leeuwis 2009). Moreover, earlier – mostly qualitative – research with such a broad scope typically focused on the variety of functions systemic intermediaries may play when developing research or transition agendas. Our study has linked these lines of inquiry by investigating SII concerned with actually implementing collective R&D agendas (i.e. setting up collaborative R&D projects). Although some authors have studied firm-level technology support and business development in a transitions context, see e.g. Kanda et al.'s work on boosting eco-innovation (Kanda et al. 2018), so far little attention has been paid to intermediaries tasked with coordinating cumulative research efforts fitting a widely backed research agenda. The interest for this kind of agents is likely to be growing, as it is increasingly understood that innovation endeavours with a transformative ambition require alignment of research efforts that may result in the exploration as well as exploitation of promising innovation paths (Boon and Edler 2018; Schot and Steinmueller 2019). Intermediaries like SII have been named as a main building block for the next generation of innovation policy (Kuhlmann and Rip 2018). Second, by also drawing on research concerning the determinants for R&D collaboration

(Savino, Messeni Petruzzelli, and Albino 2017), we contribute to the literature on the potential of SII to steer inter-organisational knowledge recombination. Our discussion on the rebalancing of proximity effects has pointed at various trade-offs, paving the way for more research on the possibilities and constraints of SII as a policy tool.

5.3. Policy implications

Overall, the industry-specific SIIs investigated here appear to consolidate and unite rather related sub-networks. Firms within the scope of a TKI are facilitated to tap into distinct knowledge bases of partners which are located further, but accessible through existing social (R&D network) structures. Collaborations crossing the boundaries of the TKI's scope, however, remain relatively sensitive to cognitive proximity. This latter observation underlines a concern expressed by Howells already in 2006, stating that the strong presence of intermediary institutions in The Netherlands might in fact create inertia rather than disruption (Howells 2006). Or, stated less alarming, new partnership formation between firms subjected to the same TKI possibly occurs mainly on the basis of a related R&D diversification strategy: firms are able to diversify by accessing knowledge that is new to them, but still relatively related to their current knowledge base and partnership networks.

Apparently, knowledge development trajectories in The Netherlands are constrained by some degree of path-dependency. This is consistent with Frenken's (2017) conjecture that in practice, policy for collaborations and R&D often are particularly suited for related diversification strategies. Ideally, governments attempt to steer at both a related and unrelated diversification strategy, which will provide the platform for both incremental and radical innovation that can benefit the economy and society in the long run (Frenken 2017; Castaldi, Frenken, and Los 2015). Our evidence suggests that the suitability of industry-specific SII depends on the policy goal in mind. In case the objective is to create incremental innovation, spurred by mostly large (incumbent) firms, the use of sectoral intermediaries and bottom-up research agenda setting seems appropriate. On the other hand, when supposed to ignite breakthrough innovation based on the combination of distant knowledge, an intermediary-based policy strategy would probably need to show more convincing results.

5.4. Shortcomings and further research

Looking at the research design, a clear weakness is the lack of a sound control group. As the policy is applied at the national level, no comparable set of firms exists. This is a common issue in researching and evaluating policy (Isserman and Merrifield 1982). Our baseline and SII analyses shed light on associations that can be further studied with more rigorous data collection (Mann 2003). Replication studies could also address the possible non-linear effects as well as substitution possibilities and complementarities between proximities (Boschma 2005; Capaldo and Messeni Petruzzelli 2014). All of these interactions and dynamics have been left out of this first exploration of the potential of SII.

Two avenues stand out when it comes to possibilities for further research. Not only does it seem important to repeat this study in similar contexts; we also advice to consider the effects of other types of SII. It is probable that some of the observed dynamics are particular for industry-specific SII representing sub-networks residing in the overall knowledge

system. Besides those 'vertically' organised intermediaries one could also inspect the impact of SII devoted to more horizontal themes. For instance, they occasionally play a role in experimental spaces in which temporarily formed communities (composed of actors from different fields) explore particular new technologies or other innovation-related developments (Cartel, Boxenbaum, and Aggeri 2018; Mair, Martí, and Ventresca 2012). While it has been hypothesised that such places may act as platforms for bringing together firms from unrelated specialisations (Janssen, and Frenken 2019), there is no sound analysis available showing whether this is truly the case. Similarly, there is a policy trend going on in which systemic intermediaries orchestrate knowledge networks not only by being a broker, but also by pro-actively putting societally relevant topics on the research agenda. Various scholars have looked into the potential of SII to contribute to path creation for, e.g., energy transitions (van Lente et al. 2003; Kivimaa 2014; Kanda et al. 2018; Gliedt., Hoicka, and Jackson 2018; Kivimaa et al. 2019) but again it remains unknown whether this can also be combined with spurring distant and therefore promising knowledge flows. On a methodological note, as skill-relatedness appeared to be a sound predictor of R&D collaboration, using this proxy for cognitive proximity is viable for such follow-up studies on the additionality of policies spurring uncommon knowledge exchange.

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Appendix

Table A1. Overview of variables.

Type	Concept	Name	Description	Measurement
Dependent	Partnership formation		Collaboration between firms i and j at t_0	(1) if firms i and j form a partnership by participating in at least one project together at t_0; (0) otherwise.
	New partnership formation		Collaboration between firms i and j at t_1	(1) if firms i and j form a new partnership by participating in at least one project together at t_1; (0) otherwise. Existing partnerships are excluded.
Independent	Geographical proximity	Geographical proximity	Inverse of geographical distance between firms i and j	Inverse distance in 100km 'as the crow flies' between addresses of firms i and j.
	Cognitive proximity	Skill-relatedness	Skill-relatedness between firms i and j	Measured following the method by Neffke, Otto, and Weyh (2016). When skill-relatedness is high, ~1. If no relatedness, 0. Most unrelated, ~ −1
	Social proximity	Network proximity	Shortest path between firms i and j	Inverse geodesic distance between firms i and j in baseline R&D network (t0).
		Shared partners	Number of direct partners that i and j have in common	Count of the number of partners that i and j have in common in baseline R&D network (t0).
	Organisational proximity	Firm types *(3 dummy variables)*	Whether firms i and j are both SME, both Large or SME and Large	Categorical variable with three levels respectively: both SME firms, both large firms, and one SME with one large firm. The latter is the baseline level.
		Research types *(3 dummy variables)*	Whether firms i and j are both involved in fundamental research, neither of them, or just one	Categorical variable with three levels respectively: both applied research, both fundamental research, and one applied research firm with one fundamental research firm. The latter is the baseline level.
	Systemic innovation intermediary (SII)	Same TKI	Whether firms i and j are subjected to the same TKI	(1) if firms i and j have both participated in at least one t0 project registered under the same TKI, (0) otherwise.
Control	R&D potential	Mean projects	Number of projects that i and j participated in	Mean number of project participations for i and j at t_0.
	Collaboration potential	Mean partners	Mean number of project partners for i and j	Mean number of unique partners (degree) for i and j in the network at t_0.
	Collaboration propensity	Same industry	Dummy indicating whether i and j are in same industry	(1) if 2-digit NACE code of i and j is identical, (0) otherwise.

Table A2. Descriptive statistics of variables used in datasets for tie-formation regression models.

	Model 1: All possible ties at t_0				Model 2–4: All possible ties at t_1				Model 5: Possible Same-TKI ties at t_1				Model 6: Possible Cross-TKI ties at t_1			
Numeric variables	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Geographical proximity (Geo)	−0.894	−3.19	0	0.509	−0.896	−3.19	0	0.508	−0.886	−3.17	0	0.529	−0.897	−3.19	0	0.505
Skill relatedness (Cog)	−0.033	−1	1	0.585	−0.037	−1	1	0.583	0.183	−1	1	0.615	−0.068	−1	1	0.572
Network proximity (Soc)					−3.374	−2	−7	0.906	−2.560	−2	−6	0.742	−3.486	−2	−7	0.868
Shared partners (Soc)					0.204	0	11	0.520	0.802	0	11	0.973	0.121	0	6	0.348
Mean project					1.829	1	23	1.805	2.183	1	23	2.415	1.780	1	22	1.699
Mean partners					8.357	1	54	4.872	9.995	1	54	6.421	8.132	1	44	4.573
Categorical variables	Perc. 0 (%)		Perc. 1 (%)		Perc. 0 (%)		Perc. 1 (%)		Perc. 0 (%)		Perc. 1 (%)		Perc. 0 (%)		Perc. 1 (%)	
$Y(t_0)$	98.86		1.14													
$Y(t_1)$					99.86		0.14		99.42		0.58		99.92		0.08	
Both SME (Org)	40.35		59.65		40.29		59.71		38.33		61.67		40.57		59.43	
Both large firms (Org)	94.85		5.15		94.96		5.04		93.88		6.12		95.11		4.89	
SME with large firm (Org)	64.79		35.21		64.74		35.26		67.80		32.20		64.32		35.68	
Both applied research (Org)					36.67		63.33		31.82		68.18		37.34		62.66	
Both fundamental research (Org)					95.97		4.03		94.01		5.99		96.24		3.76	
Applied research firm with fundamental research firm (Org)					67.35		32.65		74.17		25.83		66.42		33.58	
Same TKI					87.91		12.09		0		100		100		0	
Same industry	93.19		6.81		93.38		6.62		84.48		15.52		94.61		5.39	

Table A3. Correlations for the numeric variables in dataset with ties formed at t_0.

Variable		[1]	[2]	[3]
[1]	Skill relatedness	1		
[2]	Geographical proximity	0.041	1	
[3]	Dummy same industry	0.346	0.022	1

Table A4. Correlations for the numeric variables in dataset with ties formed at t_1.

Variable		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
[1]	Same TKI	1							
[2]	Skill relatedness	0.140	1						
[3]	Network proximity	0.334	0.069	1					
[4]	Shared partners	0.427	0.079	0.594	1				
[5]	Geographical proximity	0.007	0.039	0.062	0.042	1			
[6]	Mean projects	0.073	0.001	0.196	0.214	0.003	1		
[7]	Mean partners	0.125	0.003	0.207	0.216	0.049	0.662	1	
[8]	Dummy same industry	0.133	0.341	0.065	0.061	0.020	−0.018	0.010	1

Table A5. Correlations for the numeric variables in sample of Same-TKI ties.

Variable		[1]	[2]	[3]	[4]	[5]	[6]	[7]
[1]	Skill relatedness	1						
[2]	Network proximity	0.013	1					
[3]	Shared partners	0.043	0.621	1				
[4]	Geographical proximity	0.006	0.095	0.089	1			
[5]	Mean projects	0.004	0.209	0.258	0.033	1		
[6]	Mean partners	0.026	0.168	0.246	0.081	0.722	1	
[7]	Dummy same industry	0.424	−0.051	−0.005	−0.044	−0.056	0.013	1

Table A6. Correlations for the numeric variables in sample of Cross-TKI ties.

Variable		[1]	[2]	[3]	[4]	[5]	[6]	[7]
[2]	Skill relatedness	1						
[3]	Network proximity	0.025	1					
[4]	Shared partners	0.015	0.596	1				
[5]	Geographical proximity	0.043	0.060	0.031	1			
[6]	Mean projects	−0.012	0.182	0.190	−0.004	1		
[7]	Mean partners	−0.023	0.181	0.161	0.042	0.643	1	
[8]	Dummy same industry	0.311	0.036	0.011	0.034	−0.019	−0.013	1

Table A7. Descriptive statistics of the Dutch public-private R&D network in t_0 and t_1.

	2013 (t_0)	2014-2016 (t_1)
Projects	381	531
Actors	674	674
– of which firms	589	589
Possible ties	173,166	171,198
Actual collaborations (ties)	3,172	3,813
– of which interfirm ties	1,968	2,213
New ties at t_1	-	641
– of which interfirm ties	-	245
Total network density	0.014	0.017
Mean degree (number of unique partners)	9.413	11.315
Min degree	1	1
Max degree[a]	175	218
Mean tie weight (collaboration intensity)	1.282	1.299
Min tie weight	1	1
Max tie weight	15	15
Mean shortest path length	3.296	2.958
Longest shortest path	7	6