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Abstract

This paper analyses how the formation of collaboration networks affects firm-level innovation by applying the 'Goldilocks principle'. The 'Goldilocks principle' of optimal distance in innovation networks postulates that the best firm-level innovation results are achieved when the partners involved in the network are located at the 'right' distance, i.e. 'not too close and not too far' from one another, across non-geographical proximity dimensions. This principle is tested on a survey of 542 Norwegian firms conducted in 2013, containing information about firm-level innovation activities and key innovation partners. The results of the ordinal logit regression analysis substantiate the Goldilocks principle, as the most innovative firms are found amongst those that collaborate with partners at medium levels of proximity for all non-geographical dimensions. The analysis also underscores the importance of the presence of a substitution-innovation mechanism, with geographical distance problems being compensated by proximity in other dimensions as a driver of innovation, whilst there is no support for a potential overlap-innovation mechanism.

Keywords

Proximities, innovation, networks, collaboration, Goldilocks principle, Norway

JEL Codes

O31, O33, D85

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1. Introduction

'Open' strategies, which allow the outflow and inflow of knowledge and resources across organisational boundaries, are considered essential for innovation (Chesbrough 2003; Enkel, Gassmann, and Chesbrough 2009). In a gradually more interlinked world, the formation of external networks with partners, such as knowledge-intensive strategic alliances, is increasingly regarded as an important driver for the generation and diffusion of knowledge and, consequently, for innovation (Narula and Hagedoorn 1999; Huggins et al. 2012). Yet, despite the growing weight awarded to networks in innovation research, we still know relatively little about the motives and the characteristics of the actors involved in innovation networks (on both an individual and organisational level) and about how these characteristics are related to changes in innovation performance (Capaldo and Petruzzelli 2014). Within this context, the role of distance in the formation and success of networks has come under closer scrutiny. While trying to understand how geographical distance shapes innovation has been a classic object in economic geography, recent research has put the emphasis on alternative types of proximity, such as social, organisational, institutional, or cognitive (Boschma 2005; Crescenzi et al. 2016; Lagendijk and Oinas 2005; Lagendijk and Lorentzen 2007; Torre and Rallet 2005).

Distance has more dimensions than a purely geographical one. These include, at least, cognitive, organisational, social, , and institutional dimensions. The growing consensus is that collaboration for innovation requires, in order to be successful, a certain level of proximity which extends beyond pure physical contiguity and involves proximity in a number of non-geographical forms. However, how much proximity is needed is subject to debate (Rodríguez-Pose, 2011). Whilst, on the one hand, proximity can be critical for facilitating efficient and effective interaction between actors, on the other, too much proximity can hamper innovation as it reduces the scope for novelty and learning. This tension has been called the 'proximity paradox' by Boschma and Frenken (2010): different proximities are a necessary precondition for knowledge generation and diffusion, but excessive proximity or, conversely, too much distance can be harmful for innovation. Being too close or being too far can both reduce the scope for learning.

In order to resolve this apparent paradox, we introduce in this paper the developmental psychology and cognitive science notion of the 'Goldilocks principle' of non-geographical distance in innovation networks. This principle posits that for innovation networks to yield the greatest returns, partners involved in the network should be 'not too close and not too far', but rather located at a distance in the cognitive, organisational, social, and institutional spectrum which is just right. This implies an optimal level of proximity that lies somewhere in between the extremes of very high and very low proximity.

While this principle has not been formally formulated before, an increasing number of contributions have sought to test different aspects of it empirically (e.g. Aguiléra et al. 2012; Broekel and Boschma, 2012; Crescenzi et al. 2016; Feldman et al. 2015; Marrocu et al. 2013; Nooteboom et al. 2007; Rigby 2015). However, as discussed below, it is often the case that empirical tests rely on rather crude indicators, which, in turn, make strong assumptions about the relationships between sectors, places, and organisations.

Our research aims to overcome this problem, by measuring different types of proximities in a more straightforward and direct way, involving asking firm managers about their perception of the distance to their most important partner across each non-geographical dimension. We investigate the role of various types of proximity by examining possible interrelationships between them and by considering the distributions of proximity levels instead of merely looking at average values. The objective is to assess firm-level innovation in terms of new-to-firm and new-to-market product innovation for companies that collaborate with partners at different levels of distance in each dimension, relative to firms that do not collaborate with any partners.

The data are based on matched information from two surveys of Norwegian firms, conducted in 2013. In these surveys, firms were asked about their innovation activities and about their most important partners in the innovation process. The sample covers 542 firms with more than ten employees across all industries and all regions of Norway.

The results confirm the basic proposition of the Goldilocks principle that a medium level of non-geographical distance to partners is best in order to generate different types of innovation. Firms operating at the 'right' distance ('not too close, not too far') outperform those engaged in collaboration at both lower and higher levels of cognitive, social, and institutional distance. Such firms are significantly more likely to introduce new products. Our findings also suggest that geographical proximity to partners is not significantly correlated with any of the non-geographical distance dimensions. However, there is a considerable degree of interaction between geographical and non-geographical proximity: firms with a low level of geographical proximity and higher levels of cognitive and institutional proximity are significantly more likely to innovate. This supports another important proposition in the literature of a substitution-innovation mechanism, whereby distance in one dimension can be compensated by proximity in at least one other dimension (Agrawal et al. 2008; Hansen 2015; Huber 2012a; Menzel 2015; Rigby 2015). There is, in contrast, no empirical support for the overlap-innovation mechanism (Hansen 2015), as the combination of high geographical proximity and high non-geographical proximity does not show a positive association with innovation.

In order to demonstrate the Goldilocks principle, the paper proceeds as follows. First, section 2 provides an overview of the relevant theoretical debates. Section 3 outlines the research methods and introduces the novel dataset used in the analysis. The empirical results are presented in section 4 and the paper concludes with a discussion of the results in section 5.

2. Theoretical framework

Proximity for innovation

Geographical proximity is generally considered as beneficial for inter-organisational collaboration and innovation (Moulaert and Sekia 2003). Within this context, it has been argued that the possibilities of face-to-face interaction reduce coordination costs and facilitate the transfer of tacit knowledge (Howells 2002; Lawson and Lorenz 1999; Storper 1997). In general, proximity is regarded as an important factor for innovation (Knoben and Oerlemans 2006). This is usually based on the view that a certain form of proximity is required for successful knowledge interactions and that proximity between organisations facilitates knowledge interactions by expediting coordination and reducing uncertainty (Boschma 2005). Proximity refers to closeness of actors and is often assessed by the similarity between the actors involved in the network. Importantly, recent work on proximity has emphasised that, on top of geographical proximity, other types of proximity, including organisational, social, cognitive, or institutional proximity, play an essential role in determining the returns to collaboration in terms of increased innovativeness and competitiveness of firms (Amisse et al. 2012; Boschma 2005; Crescenzi et al. 2016; Franco et al. 2014; Gertler 2004; Lagendijk and Lorentzen 2007; Lagendijk and Oinas 2005; Mattes 2012; Torre and Rallet 2005; Zeller 2004). Whilst these concepts have been defined and operationalised in various ways (see section 3 below), in this paper we follow the definitions of different types of proximity proposed by Boschma (2005) and Boschma and Frenken (2010).

Social proximity refers to the strength of interpersonal links.[1] This notion has been influenced by the embeddedness literature (Granovetter 1985; Uzzi 1996), which has stressed the importance of social context for economic action. From this perspective, trust-based ties, relying on friendship or repeated interaction, can facilitate knowledge interaction for innovation (Gertler 2004, 156).

Organisational proximity has been defined and operationalised in various ways (see section 3 below). In this paper it is operationalised as the extent to which external partnerships are organised through formal arrangements. This is based on the degree of control of organisational relations, which can range from 'on the spot' market to different levels of formal arrangements. Organisational proximity is often considered to reduce uncertainty and opportunism, which is beneficial for developing innovation networks (Boschma and Frenken 2010).

Institutional proximity refers to the extent to which the partner's norms and values are similar. The level of similarity of formal or informal institutions (North 1990) can influence inter-organisational relationships. For instance, Gertler (2004) has illustrated that national macro-level institutional differences of German versus Canadian machinery producers can affect learning and innovation. The different institutional settings of university versus industry versus government actors can similarly be a hurdle for the development of successful interaction (Etzkowitz and Leydesdorff 2000).

Finally, *cognitive proximity* refers to extent to which actors share a common knowledge base and expertise. The capacity to identify, grasp, and exploit external knowledge requires cognitive proximity (Cohen and Levinthal 1990). Cognitive proximity is vital for understanding each other in R&D alliances (Nooteboom et al. 2007) and for inventions as indicated by patent citations (Breschi and Lissoni 2009). The notion of cognitive proximity can also include sub-dimensions and similarity in terms of technical language. Huber (2012a) suggests that whereas high levels of similarity in technical

[1] This has sometimes been referred to as relational proximity (Coenen et al. 2004) or personal proximity (Schamp et al. 2004).

language are crucial, a certain degree of dissimilarity in know-how, know-what, and the way of thinking among partners can be fruitful for important inter-organisational knowledge relationships.

These types of proximities have been operationalised in various ways and often in a highly indirect fashion. One of the main contributions of this paper is that it is based on a novel dataset, where proximities are measured using dedicated survey questions to capture the meaning of the non-geographical types of proximities more directly.

The Goldilocks principle

The theoretical arguments on the importance of proximity for innovation involve intricate relationships across various dimensions (Mattes 2012). As differences in actor characteristics can make understanding each other challenging (Nooteboom et al. 2007), proximity has been argued to facilitate interactions. Yet, too much proximity may make learning new knowledge difficult, while access to heterogeneous resources and diverse knowledge has been argued to benefit innovation (Nooteboom, 2000). Hence, the exact dimension and level of different proximities is controversial: being too far apart may undermine interaction and learning, as may be exactly the case with being too close. There is therefore a need to attain an 'optimal' degree of proximity between innovative actors, in other to maximise the returns of interaction. This 'optimal' level of proximity is what we call the Goldilocks principle of non-geographical distance, i.e. partners being in the 'right range' or 'sweet spot' – not too close, not too far – to make the most of interaction.

The underlying assumptions of the Goldilocks principle as understood in this paper are that, first, collaborating with external partners is beneficial for innovation and, second, that an intermediate degree of proximity delivers the best returns to collaboration for innovation. A generalised version of the Goldilocks principle would suggest that the optimum of the medium level concerns all non-geographical types of proximities. This has occasionally been referred to as the 'proximity paradox' (Boschma and Frenken 2010). The Goldilocks principle helps resolve this apparent paradox. Just as there is no inherent contradiction in Goldilocks finding one porridge too hot and another porridge too cold, there could also be an optimal distance between partners that lies somewhere in between close proximity and long distance. This is what we refer to as the 'Goldilocks principle'.

Yet, the Goldilocks principle may only apply to certain types of proximity. Broekel and Boschma (2012) show that cognitive proximity reduces innovative performance but social proximity does not, which suggests that cognitive proximity may be most critical for the Goldilocks principle. Broekel and Boschma (2012) and Nooteboom et al. (2007) maintain that there may be an optimal level of cognitive proximity for innovation in the sweet spot between too high and too low. Overall, more empirical research is needed to shed light on the question of for which types of proximity the Goldilocks principle may apply. Furthermore, an alternative 'solution' to the proximity paradox could be that high proximity in certain dimensions may be compensated by distance in other dimensions (Boschma and Frenken 2010; Huber 2012a). That is, the optimal level of proximity in one dimension may be dependent on the levels of proximity in other dimensions.

Interrelationships: overlap mechanism or substitution mechanism

This raises the issue of how geographical proximity and the different types of non-geographical proximity are related to one another, which is an empirically under-researched question. Two theoretical perspectives can be identified in the literature: the *overlap mechanism* and the *substitution mechanism* (Hansen 2015). For analytical clarity, we suggest developing separate theoretical propositions for the respective innovation outcomes.

First, the traditional view in economic geography is that geographical proximity facilitates proximity in the other dimensions (Malmberg and Maskell 2006; Rodríguez-Pose and Crescenzi, 2008; Saxenian 1994), which subsequently is beneficial for innovation. That is, according to the *overlap mechanism*, non-geographical forms of proximity are more likely to be developed in close geographical proximity. This suggests that geographical proximity and non-geographical proximity are positively correlated. Furthermore, it has often been argued that the overlap mechanism facilitates innovation outcomes, which we call the *overlap-innovation mechanism*.

Yet, this territorial focus has been criticised. First, it has been argued that geographical proximity does not automatically lead to useful relationships between actors (Fitjar and Rodríguez-Pose 2016), for instance regarding knowledge networks (e.g. Giuliani 2007) or social proximity (e.g. Ben Letaifa and Rabeau 2013; Huber 2012b). Second, a growing number of studies illustrate that geographically distant relationships can be vital for knowledge exchange and innovation (Bathelt et al. 2004; Bathelt and Cohendet 2014; Fitjar and Huber 2015; Fitjar and Rodríguez-Pose, 2011; Herrmann et al. 2012; Knoben and Oerlemans 2012; Moodysson 2008; Trippl et al. 2009; Weterings and Ponds 2009). Yet, it remains unclear how geographically distant relationships can be maintained. Within this context, one possible argument is that non-geographical proximities may be a substitute for geographical proximity. That is, geographically distant relationships of relevance for innovation may be enabled and more easily maintained through non-geographical proximities. For instance, Capaldo and Petruzzelli (2014) show that the effect of geographical distance between partners on alliance-level innovation is contingent on organisational proximity. A generalised version would be that a compensation mechanism is in place, by which distance in one dimension can be bridged by proximity in other dimensions (Menzel 2015). Huber (2012a) empirically confirms that at least one type of proximity has to be present for the establishment and maintenance of innovation networks. This implies that geographically distant relationships are based on non-geographical types of proximity (the *substitution mechanism*). However, which type or types of non-geographical proximity are required to spur this substitution mechanism remains an unresolved empirical question. Hence, we propose a *substitution-innovation mechanism* in order to hypothesise that different combinations of geographical distance with certain non-geographical proximities are associated with innovation.

Overall, whilst recent studies have started to explore this issue (Crescenzi et al. 2016; Hansen 2015; Huber 2012a; Steinmo and Rasmussen 2016), we need more empirical research to clarify which mechanism is prevalent: the overlap or the substitution mechanism. More empirical research is also needed to test which combinations of different distances are related to innovation outcomes.

3. Methods

The paper aims to test the Goldilocks principle of 'optimal' distance in innovation networks using survey data of Norwegian firms with more than ten employees across the private sector of the economy. The survey was conducted in 2013 in two stages. First, a total of 2002 firms were interviewed by telephone by professionals working for the Ipsos MMI survey firm. The interviews were conducted with the CEO or general manager of each firm. As part of the interview, the firms were invited to participate in a follow-up web-based survey distributed by e-mail. In total, 1628 firms agreed to participate in the web-based survey, although only 542 firms actually filled in the questionnaire. The web-based questionnaire was also mainly completed by the CEO (in 80.6 percent of the cases) or other management (17.0 percent of the cases), while non-management personnel filled in only 4 questionnaires (for an additional 9 questionnaires, information on the position of the respondent within the firm is missing). The data for both parts of the survey were then matched to generate a complete data set for the companies that participated in both surveys. In the paper, the questions pertaining to proximities are drawn from the web-based survey, while the questions on innovation are from the telephone interviews. Table 1 provides descriptive statistics of the 542 firms that participated in both surveys.

Table 1: Descriptive statistics

Company size		
Median	24	
Interquartile range	30	
Mean	67.5	

Industry	*N*	*Percent*
Mining and quarrying	16	3.0
Manufacturing	119	22.0
El., gas and water supply	16	3.0
Construction	62	11.4
Trade	101	18.6
Transport and storage	31	5.7
Hotels and restaurants	29	5.4
Information and communications	28	5.2
Financial services	32	5.9
Other services	108	19.9
Total	542	100.0

Region	*N*	*Percent*
Oslo	128	23.6
Bergen	77	14.2
Stavanger	117	21.6
Trondheim	59	10.9
Rest of Norway	161	29.7
Total	542	100.0

The measure of innovation relies on a battery of questions related to the firms' product development, building on the wording of the cross-European Community Innovation Survey. We first asked whether the firms had introduced any goods or services into the market in the preceding three years that were new to the firm or significantly improved relative to their existing products. Second, we asked firms that answered affirmatively whether any of these product innovations were new to the market or whether they were only new to the firm and very similar to a product that already existed in the market. From these two questions, we derive an ordinal measure of innovation with three categories: firms without product innovations (no to the first question); firms with new-to-the-firm product innovations only (yes to the first and no to the second question); and firms with new-to-the-market product innovation (yes to both questions).

In the full data set of 2002 firms, 47.9 percent of firms reported no product innovation, 23.9 percent reported new-to-the firm innovation, and 28.2 percent new-to-the-market innovation. Innovative firms participated to a somewhat higher extent in the web-based follow-up survey, where 40.4 percent of the 542 firms participating in both surveys reported no product innovation, 27.5 percent new-to-firm innovation, and 32.1 percent new-to-market innovation.

Measuring proximity

The measures of proximity in collaboration with partners are based on an ego-network analysis with a battery of questions focusing on the firm's most important partner. The set of questions are introduced by inviting the firm representative to "think of the external partner which has been the most important for the firm's development of new products or processes during the past three years and answer in relation to the cooperation with this partner."[2] At this stage, 15.5 percent of the 542 firms that participated in the web survey indicated that they had not collaborated with any partners in the development of new products or processes. These were classified as having "no partners" and are treated as the baseline in the analysis. One of the questions pertains to the geographical

[2] The assessment of the most important partner is based on the respondent's subjective assessment of which partner has contributed the most to new product or process development (i.e. innovation). We do not have detailed information on how many partners the firm has. However, the telephone survey asked if firms collaborated with partners of seven different types (internal, suppliers, customers, competitors, consultancies, universities, and research institutes) and at three different scales (regional, national, and international). From the 21 different types of partner this potentially yields, the average firm collaborated with 5.4 types, with a standard deviation of 3.3. The first quartile was 3 types, the median 5, and the third quartile 7 types of partner. Consequently, most firms select one partner perceived as the most important from a broader portfolio of several partners.

localisation of the partner. This question is used to measure geographical proximity, which is classified as low if the partner is located within the same municipality or in the same region; as medium if the partner is located elsewhere in Norway; and as high if the partner is located outside Norway.[3]

Another set of questions covered the five non-geographical dimensions of proximity identified in Boschma's (2005) seminal paper. Most subsequent empirical analyses on the topic have focused on these five dimensions of proximity. For the most part, these have been based on register data, using either patents (e.g. Feldman et al. 2015; Rigby 2015), matched employer-employee data, or regional level data (Marrocu et al. 2013). These data sources typically provide information on only a limited number of attributes for each firm or region, meaning that the proximity dimensions tend to be captured in a fairly indirect way. Other papers use indirect indicators of proximities at an aggregated regional level (Marrocu et al. 2013). By contrast, very few papers (e.g. Broekel and Boschma 2011; Aguiléra et al. 2012) have so far used survey data to capture how the firms interpret their proximity to the partner in a more direct way. Very few studies (e.g. Hansen 2014) have measured proximities in a more detailed fashion on the basis of interviews. This paper returns to Boschma's (2005) original

[3] "Elsewhere in Norway" was selected as medium proximity as it seemed useful to differentiate between national and international collaborations from a geographic perspective. As a robustness check, we have also estimated all models treating "in the same municipality" as high proximity, "in the same region" as medium proximity, and outside the region as low proximity. These analyses show very similar results for high and medium proximity, suggesting that it is reasonable to treat local and regional partners as a single category. In a separate analysis, we estimated the models treating Norwegian partners as high proximity, other Scandinavian partners as medium proximity, and non-Scandinavian partners as low proximity. The results are similar to those reported in the paper. The levels of innovation were slightly higher for Scandinavian than (extra-regional) national partners, but firms using non-Scandinavian partners reported the highest levels of innovation. We have reported the main differences in the findings using these alternative specifications at the relevant points in the paper.

definition of each of the dimensions and suggests an alternative operationalization in which managers of the firms involved are invited to reflect on their proximity to (or distance from) their partner on each of the dimensions, building on the definitions proposed by Boschma (2005). Again, this approach relies on the respondents' subjective and qualitative assessment of the proximity to partners and we only have information provided within the questionnaire. Nonetheless, the operationalisation has attempted to translate Boschma's (2005) definition into everyday language that respondents can comprehend, as will be further outlined below.

Cognitive proximity has in previous studies typically been measured with reference to the similarity of either products or technologies across partners. Studies based on products often gaged cognitive proximity through partners' belonging to the same or different sectors or sub-sectors in studies at the firm level (Balland 2012; Balland et al. 2013) or by comparing the sectoral composition of the units in studies of macro-level units, such as regions (Marrocu et al. 2013). Other studies determined the relatedness of technologies, relying on co-classifications of patents (Feldman et al. 2015) or co-occurrences of patenting (Broekel and Boschma 2012; Crescenzi et al. 2016). In the original definition, Boschma (2005: 63) stated that "with the notion of cognitive proximity, it is meant that people sharing the same knowledge base and expertise may learn from each other". This can only be captured to a partial extent by looking at sectors or technology classes. We address the concept in a more direct fashion by asking to what extent firms agree or disagree with the statement "we share a common knowledge base and expertise with this partner".

Organisational proximity has similarly been measured in very different ways in previous literature. Some studies examined whether the partners shared similar types of organisations. For instance, Broekel and Boschma (2012) based their study on a dichotomy between profit and non-profit organisations. Others examined whether the firms belonged to the same organisation, e.g. to the same corporation or business group (Balland, 2013; Balland et al. 2013; Crescenzi et al. 2016; Marrocu et al. 2013). The latter seems to better represent the theoretical concept, where “organizational proximity is defined as the extent to which relations are shared in an organizational arrangement, either within or between operations” (Boschma, 2005: 65). However, belonging to the same corporation represents an extreme end of the spectrum of sharing organisational arrangements, where the relationship between units is not only organised in a formal agreement, but they are actually part of the same group. As we are more interested in examining cooperation across different corporations in the current paper, we focus instead on the organisation of relationships between partners and whether or not this takes the form of a formal organisational arrangement. Consequently, we build our measure on the level of agreement with the statement “our relationship with this partner is organised through formal arrangements”.

Social proximity has typically been measured in previous literature by the number of connections between places in the form of co-inventorships (Marrocu et al. 2013; Feldman et al. 2015), by previous collaboration between the organisations (Balland et al. 2013), or by whether they have any partners in common (Balland 2013). Neither of these operationalisations addresses the crucial notion of social embeddedness that Boschma attaches to this concept: “Social proximity is defined here in terms of socially embedded relations between agents at the micro-level” (Boschma, 2005: 66). This implies that we should be interested in relations that are not purely economic, but extend to the social setting, while all previous operationalisations have been based on previous or current relations among partners precisely in the economic sphere. By contrast, our definition seeks to get at the social embeddedness of relations by asking for the level of agreement with the statement that “we interact socially with the people who work in the partner’s organisation”.

Finally, institutional proximity has also been measured in different ways in previous literature. Balland (2013) proposed a similar definition to Broekel and Boschma’s (2012) operationalisation of organisational proximity above, looking at whether the organisations belong to the private sector or to a variety of non-profit sectors (government, universities, civil society). A similar approach was used by Ponds et al. (2007). Other studies simply assess institutional proximity by verifying whether the partners are from the same country (Balland et al. 2013; Hoekman et al. 2008; Marrocu et al. 2013). These are both crude ways of getting at the original definition that “institutional proximity includes both the idea of economic actors sharing the same institutional rules of the game, as well as a set of cultural habits and values” (Boschma, 2005: 68). While the earlier operationalisations may provide some indication of whether the partners are subject to the same formal rules or legal systems, they cannot say very much about the similarity of cultural habits and values. In this paper, we focus particularly on the latter aspect, gauging the level of agreement with the statement “the partner’s norms and values are similar to ours”.

For all the questions, based on a five-point Likert scale, we classify those that fully agree with the statement as having a high level of proximity to the partner, those that partly agree as medium proximity, and those that are either neutral or who disagree or strongly disagree with the statement as having a low level of proximity to the partner.[4] It is useful to go beyond merely analysing average values of proximities and consider the distribution of proximities (Broekel and Boschma 2011). Table 2 shows the distribution across the sample of firms for each of the five dimensions of proximity. In total, 359 respondents answered the question on cognitive proximity, 355 respondents answered the questions on other proximities, and 392 firms answered the question on the geographical location of the partner. Including the 84 firms that had no partners, this makes for a sample size of 439-443

[4] The three lower categories on the Likert scale are not very prevalent in the data and we therefore combined them into one category. The overall rationale of our categorisation was that the low proximity category is the below median category, high proximity is above median, while medium proximity is the median category. As a robustness check, we have also re-specified the analysis treating “neither agree, nor disagree” as medium proximity. In these analyses, medium proximity is not associated with innovation, suggesting that firms in this category are still too far from their partners and that the “optimal” distance is near the “partly agree” category.

firms for non-geographic proximity and 476 firms for geographic proximity. The remainder of the 542 firms have missing values on the proximity variables.[5]

Table 2: Frequency distribution for the proximity dimensions

Dimension	Measure	No partners	Low proximity	Medium proximity	High proximity	N
Cognitive proximity	We share a common knowledge base and expertise with this partner	19.0 %	16.0 %	30.0 %	35.0 %	443
Organisational proximity	Our relationship with this partner is organised through formal arrangements	19.1 %	16.0 %	19.1 %	45.8 %	439
Social proximity	We interact socially with the people who work in the partner's organisation	19.1 %	49.9 %	18.9 %	12.1 %	439
Institutional proximity	The partner's norms and values are similar to ours	19.1 %	19.1 %	30.1 %	31.7 %	439
Geographic proximity	Where is the partner located?	17.7 %	17.9 %	23.3 %	41.2 %	476

Overall, Norwegian firms declare high levels of proximity to their partners. High proximity is the modal category in four of the five dimensions. Low proximity is the least common response in each of these dimensions. The exception is social proximity, where nearly half of the firms (49.9 percent) state that they do not interact socially with their partners. Conversely, 45.8 percent express a high level of organisational proximity, implying that the relationship is shared in a formal organisational arrangement. Almost as many – 41.2 percent – collaborate with partners that are geographically close. More than a third of firms also state a high level of cognitive proximity with their partners, and only 16 percent classify their cognitive proximity as low. Nearly a third of firms collaborate with

[5] As a robustness check, we have estimated all models for the sub-sample of 410 firms that responded to all the proximity questions. These analyses show very similar results to those reported in the paper. They can be made available upon request.

partners with very similar norms and values to themselves, signifying a high level of institutional proximity.

4. Analysis

The Goldilocks principle rests on two main assumptions. First, firms may benefit from collaborating with external partners in innovation processes. Second, the returns to collaboration depend on the proximity between the partners, with a medium level of proximity delivering the best results. These assumptions are tested in the following sections through bivariate analyses using contingency tables and multivariate analyses using ordinal logit regressions. In both cases, the analyses compare firms that collaborate with external partners at different levels of proximity with firms that do not collaborate with external partners.

Is proximity to partners associated with levels of innovation?

The first set of analyses presents the bivariate correlations between the levels of proximity and the three product innovation outcomes. Table 3 shows five sets of contingency tables, one for each dimension of proximity. For illustrative purposes, Figure 1 shows the same data as a bar chart, showing total innovation (new-to-firm plus new-to-market) in the top panel and new-to-market innovation in the bottom panel. The data are consistent with the first assumption of the Goldilocks principle: the category “no partners” regularly has the lowest share of firms producing new-to-market innovations and the highest share of firms which failed to introduce any product innovation at all. For most dimensions of proximity, the data are also consistent with the second assumption. In all the non-geographical dimensions of proximity, the highest share of new-to-market innovators can be found among those that collaborate with partners at medium levels of proximity. For cognitive, organisational, and social proximity, firms with partners at medium proximity also report the highest level of innovation overall. Geographical proximity displays a different pattern, with firms collaborating with partners at a longer distance being most likely to innovate and to introduce new-to-market innovation. All bivariate correlations display statistically significant associations between the variables, with chi-squared tests significant at the 99 percent level or more.

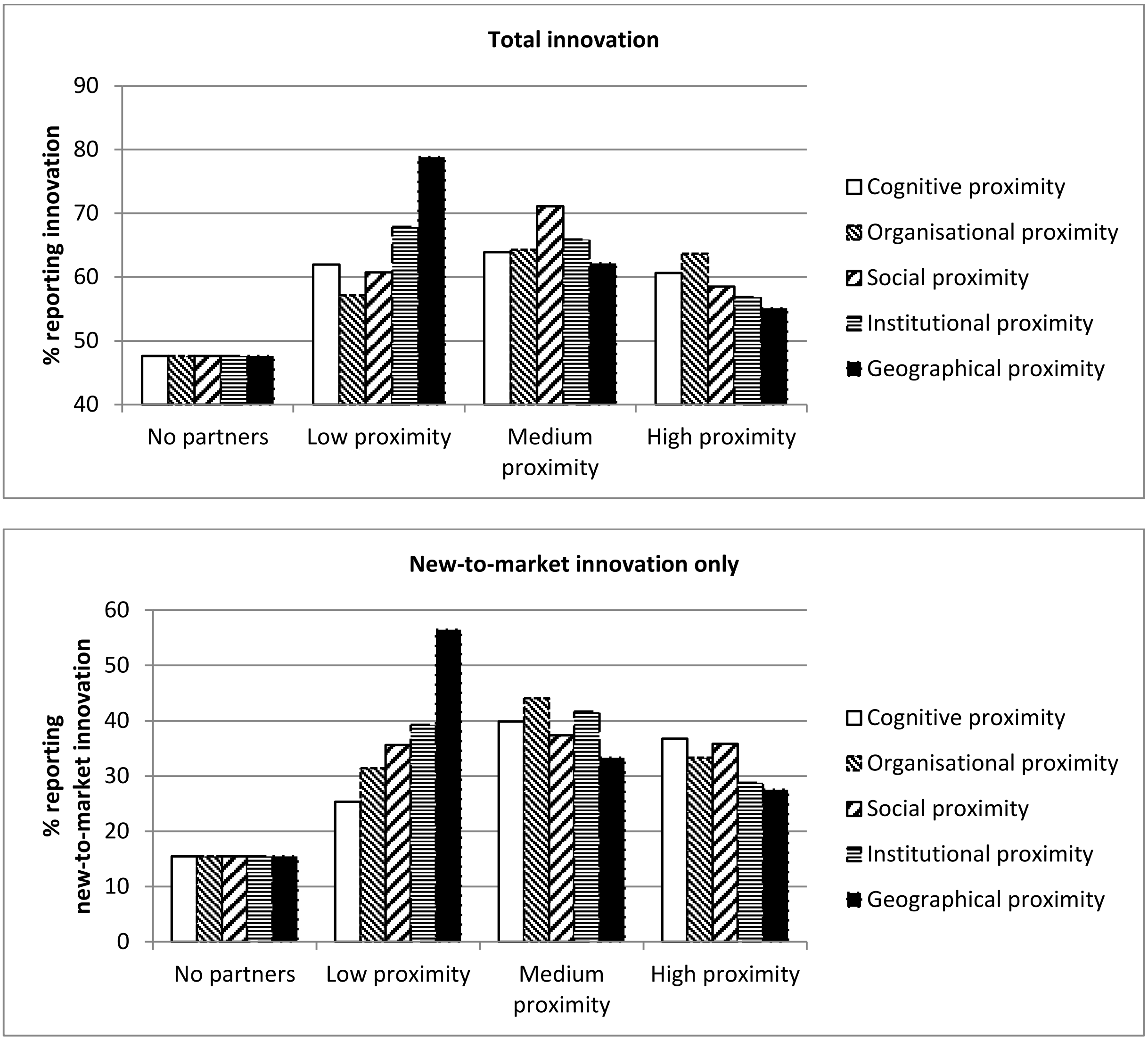
There is, however, some diversity across the different dimensions when it comes to the strength of the associations and in particular the differences between the three levels of proximity in terms of the innovation outcomes. The largest differences in the share of innovative firms can be found in the geographical proximity dimension. Firms that collaborate with partners at low geographical proximity introduce new-to-market products more than twice as frequently as those that collaborate with partners located at high proximity and 1.7 times as frequently as those that collaborate with partners at medium proximity.

For the non-geographical dimensions, the differences are more muted. Indeed, the share of new-to-market innovators is almost identical across all levels of social proximity, although the overall share of innovators is more than 10 percentage points higher at medium levels of proximity. For cognitive proximity, the overall share of innovators is similar across the three levels, but firms with partners at medium and high proximity report a higher share of new-to-market innovations. For organisational proximity, the share of innovative firms is also similar for medium and high proximity, although firms with medium proximity introduce more new-to-market innovations by more than 10 percentage points. For institutional proximity, there are very small differences in the levels of innovation for firms with low and medium proximity to partners, whereas those with high proximity introduce innovations at a lower rate of around 10 percentage points, both overall and for new-to-market innovation specifically.

Table 3: Proximity to partner and product innovation, contingency tables

Type of proximity	No innovation	New to firm	New to market	N
	Product innovation (row percentages)			
Cognitive proximity				
No partners	52.38	32.14	15.48	84
Low proximity	38.03	36.62	25.35	71
Medium proximity	36.09	24.06	39.85	133
High proximity	39.35	23.87	36.77	155
Total	40.63	27.54	31.83	443
$\chi^2 = 19.70$, df = 6, P = 0.003				
Organisational proximity				
No partners	52.38	32.14	15.48	84
Low proximity	42.86	25.71	31.43	70
Medium proximity	35.71	20.24	44.05	84
High proximity	36.32	30.35	33.33	201
Total	40.32	28.02	31.66	439
$\chi^2 = 18.43$, df = 6, P = 0.005				
Social proximity				
No partners	52.38	32.14	15.48	84
Low proximity	39.27	25.11	35.62	219
Medium proximity	28.92	33.73	37.35	83
High proximity	41.51	22.64	35.85	53
Total	40.09	27.79	32.12	439
$\chi^2 = 17.53$, df = 6, P = 0.008				
Institutional proximity				
No partners	52.38	32.14	15.48	84
Low proximity	32.14	28.57	39.29	84
Medium proximity	34.09	24.24	41.67	132
High proximity	43.17	28.06	28.78	139
Total	40.09	27.79	32.12	439
$\chi^2 = 20.01$, df = 6, P = 0.003				
Geographical proximity				
No partners	52.38	32.14	15.48	84
Low proximity	21.18	22.35	56.47	85
Medium proximity	37.84	28.83	33.33	111
High proximity	44.9	27.55	27.55	196
Total	40.34	27.73	31.93	476
$\chi^2 = 37.86$, df = 6, P < 0.001				

Figure 1: Share of firms reporting innovation, by proximity to partner



Is the association between proximity and innovation robust to controls?

The second set of analyses examines the association between each of the proximity dimensions and the levels of innovation through a set of multivariate ordinal logit regressions. The purpose is to control for potentially confounding variables, such as the size, sector, and technological sophistication of the firm. In the analysis, product innovation is defined as the dependent variable; a dependent variable with three levels: i) no innovation, ii) new-to-firm innovation, and iii) new-to-market innovation. The independent variable of interest is collaboration with partners at different levels of proximity, which is introduced in the form of dummy variables for collaboration with partners at low, medium, and high proximity, respectively. The coefficient for each dummy variable represents the difference in the log odds of having a higher level of product innovation for firms in this category compared with those that do not collaborate with any partners.

We run five different models, one for each dimension of proximity. This is done for two reasons. First, because 'no partners' is the baseline for all the five proximity variables, including several of these variables in the same model would require selecting a different baseline for all except one of them, meaning that this category could not be compared with the 'no partners' category. Second, this method has the advantage of preventing the inclusion of too many variables relative to the number of units in the model. This is important as all the non-geographical proximity dimensions are fairly strongly correlated (Pearson's R is in the range of 0.60 to 0.76 for the bivariate correlations between these four variables).

The analyses further control for a number of factors which may be expected to affect a firm's innovation output and could influence the results. The controls include: the number of employees in the firm; the share of employees with a tertiary level of education; and the level of investments in R&D as a share of the firm's total revenue. As the distribution of all these three variables is highly skewed, they are expressed as natural logarithms in the estimations. We also control for the share of firm ownership by foreign stockholders and for the industry of the firm, measured as a set of fixed effects for the following sectors: mining and quarrying; manufacturing; utilities; construction; wholesale and retail trade; food and accommodation services; transportation and storage services; information and communication services; financial and insurance services; and other services.

The model takes the following form:

$$\text{logit}[\Pr(\text{Innovation}_i > j)] = \alpha_j + \beta_1 \, \mathbf{Proximity}_i + \beta_2 \, \mathbf{Controls}_i + \varepsilon_i \qquad (1)$$

j = {No innovation < New-to-firm innovation < New-to-market innovation}

In this model, the probability of firm *i* having a level of product innovation higher that the *j*th category depends on the two vectors of proximities and control variables explained above. The model also includes a cut-off point a_j for each of the two lowest values of the dependent variable and a random error term ε with logistic distribution. Table 4 shows the results of fitting model (1) for each of the five proximity dimensions. The sample size is somewhat lower than in Tables 2 and 3 as, in the sample of 542 firms, 30 have missing values for R&D expenditure and 12 have missing values for the share of educated workers.

Table 4: Proximity to partner and product innovation, ordinal regression analyses

	Proximity type				
	Cognitive	**Organisational**	**Social**	**Institutional**	**Geographical**
Baseline: No partners					
Low proximity	0.10 (0.33)	0.37 (0.34)	0.29 (0.27)	0.37 (0.32)	1.01*** (0.36)
Medium proximity	0.51* (0.30)	0.45 (0.33)	0.63** (0.32)	0.55* (0.30)	0.51* (0.30)
High proximity	0.40 (0.29)	0.38 (0.28)	0.41 (0.37)	0.27 (0.29)	0.18 (0.27)
Log no. of employees	0.09 (0.11)	0.10 (0.11)	0.09 (0.11)	0.09 (0.11)	-0.03 (0.12)
Log % of tertiary education	0.27*** (0.09)	0.27*** (0.09)	0.26*** (0.09)	0.26*** (0.09)	0.27*** (0.09)
R&D expenditure	0.57*** (0.11)	0.56*** (0.11)	0.59*** (0.11)	0.59*** (0.11)	0.68*** (0.11)
Share of foreign ownership	0.65** (0.29)	0.63** (0.29)	0.67** (0.29)	0.68** (0.29)	0.28 (0.29)
Industry fixed effects	Included	Included	Included	Included	Included
Cut 1	1.90 (0.52)	1.97 (0.52)	1.95 (0.52)	1.95 (0.52)	1.57 (0.52)
Cut 2	3.32 (0.54)	3.40 (0.54)	3.38 (0.54)	3.38 (0.54)	3.06 (0.54)
N	416	413	414	414	445
Log likelihood	-397.37	-397.83	-395.92	-396.17	-418.18
Pseudo-R^2	0.12	0.11	0.12	0.12	0.14

Note: The numbers in brackets refer to standard errors of the coefficients.

*: P < 0.10, **: P < 0.05, ***: P < 0.01

The results of the regression analyses are consistent with those from the bivariate analyses insofar as collaborating with partners at medium level of proximity is associated with a significantly higher probability of innovating in four of the five dimensions: cognitive, social, institutional, and geographical proximity. The coefficient is relatively similar in all cases, ranging from 0.51 to 0.63, which corresponds to between 67 and 88 percent higher log odds of belonging to a higher category than if the firm has no partners. Organisational proximity is the only dimension in which partners at medium proximity do not provide a statistically significant benefit, although the coefficient remains positive. Furthermore, there is a strong and significant positive effect of collaborating with geographical partners at low proximity, which is also consistent with the bivariate analyses. This relationship also has the highest coefficient at $\hat{\beta} = 1.01$, which corresponds to 175 percent higher log odds of innovating. Conversely, collaborating with partners at high proximity does not yield significantly better results than having no partners at all in any of the dimensions. The same is true for collaboration at low proximity in all dimensions other than geographical proximity. It is worth noting that the significance tests reported in the analyses are based on comparisons against the baseline of no partners, i.e. the hypothesis that the coefficient is equal to zero, and hence this does not indicate that the coefficients are significantly different from each other. Nonetheless, the analyses show that collaboration with partners at medium cognitive, social, and institutionaldistance and at medium or low geographical proximity are the only types which are associated with significantly higher levels of product innovation.

Is there an association between geographical and non-geographical proximity dimensions?

The next question we address is whether the geographical and non-geographical proximity dimensions are related. A central motivation for the contribution by Boschma (2005) was to uncover why geographical proximity is related to interactive learning. Boschma (2005) argued that geographical proximity facilitates the development of proximity in other dimensions. On this basis, a positive association between geographical and non-geographical dimensions of proximity could be expected. This is the so-called overlap mechanism. However, other researchers have instead argued for a substitution mechanism, whereby firms develop closer relationships in one or more other dimensions of proximity to compensate for increased geographical distance (Huber 2012a; Menzel 2015).

In order to examine this relationship, Table 5 shows four sets of contingency tables between each of the non-geographical proximity dimensions and geographical proximity. The tables illustrate the share of firms for each level of geographical proximity that have low, medium, and high proximity to their partner on the non-geographical dimension. Overall, the tables show neither a statistically significant positive nor a negative association between geographical and non-geographical proximity. The chi-squared tests for all associations show non-significant results. However, the patterns tend to support the presence of a negative rather than a positive association, as the share of partnerships with high cognitive, organisational, and social proximity is higher among partners with low geographical proximity than among partners with medium or high geographical proximity.[6]

[6] In one of the robustness checks, we ran the analyses using “elsewhere in Scandinavia” as the medium category, as reported in footnote 3. These analyses show a significant association between geographic proximity and social and institutional proximity (at the 95 percent level), as well as cognitive proximity (at the 90 percent level).

Table 5: Geographical and non-geographical proximity, contingency tables

	Geographical proximity (column percentages)			
Type of proximity	**Low proximity**	**Medium proximity**	**High proximity**	**N**
Cognitive proximity				
Low proximity	11.69	24.21	22.84	69
Medium proximity	40.26	30.53	38.27	122
High proximity	48.05	45.26	38.89	143
Total	100.00	100.00	100.00	334
χ^2 = 6.53, df = 4, P = 0.163				
Organisational proximity				
Low proximity	13.16	18.75	25.79	69
Medium proximity	23.68	22.92	22.64	76
High proximity	63.16	58.33	51.57	186
Total	100.00	100.00	100.00	331
χ^2 = 5.58, df = 4, P = 0.233				
Social proximity				
Low proximity	51.32	66.67	63.52	204
Medium proximity	30.26	22.92	21.38	79
High proximity	18.42	10.42	15.09	48
Total	100.00	100.00	100.00	331
χ^2 = 5.50, df = 4, P = 0.240				
Institutional proximity				
Low proximity	33.77	21.05	20.13	78
Medium proximity	29.87	37.89	40.88	124
High proximity	36.36	41.05	38.99	129
Total	100.00	100.00	100.00	331
χ^2 = 6.38, df = 4, P = 0.173				

The analyses in Table 5 examine whether there is an association between having partners at low or high levels of geographical proximity and the non-geographical proximity to partners. While there is no evidence of such an association, there may still be a relationship between the dimensions, as firms that combine geographical and non-geographical proximities in certain ways may be more likely to innovate. In order to examine this relationship, we respecify model (1) to include an interaction between geographical and non-geographical proximity dimensions. The model is based on equation (1):

logit[Pr($Innovation_i$>j)] = $\alpha_j + \beta_1$ **PROXIMITY**$_i$ + β_2 **Controls**$_i$ + ε_i

j = {No innovation < New-to-firm innovation < New-to-market innovation}

However, in this case **PROXIMITY** is a vector representing a matrix of different combinations of geographical and non-geographical proximity, which is defined as follows:

$$\boldsymbol{PROXIMITY} = \begin{bmatrix} proximity_{low\ low} & proximity_{low\ medium} & proximity_{low\ high} \\ proximity_{medium\ low} & proximity_{medium\ medium} & proximity_{medium\ high} \\ proximity_{high\ low} & proximity_{high\ medium} & proximity_{high\ high} \end{bmatrix}$$

Table 6 shows the results of fitting this model to the data. We run four models, one for each of the non-geographical proximity dimensions.

Table 6: Interaction between geographical and non-geographical proximities and product innovation, ordinal regression analyses

	Cognitive	Organisational	Social	Institutional
Baseline: No partners				
*Low proximity * Low geographical proximity*	-0.24	1.70**	0.83*	0.72
	(0.72)	(0.80)	(0.44)	(0.48)
*Medium proximity * Low geographical proximity*	1.09**	0.02	1.19**	1.14**
	(0.46)	(0.56)	(0.50)	(0.52)
*High proximity * Low geographical proximity*	1.06**	1.18***	0.83	1.07**
	(0.46)	(0.42)	(0.63)	(0.51)
*Low proximity * Medium geographical proximity*	0.53	0.32	0.31	-0.13
	(0.46)	(0.54)	(0.35)	(0.52)
*Medium proximity * Medium geographical proximity*	0.30	0.80	0.54	0.91**
	(0.46)	(0.50)	(0.47)	(0.41)
*High proximity * Medium geographical proximity*	0.56	0.48	1.68**	0.51
	(0.39)	(0.36)	(0.69)	(0.40)
*Low proximity * High* ***geographical proximity***	-0.02	0.09	0.11	0.58
	(0.40)	(0.40)	(0.31)	(0.42)
*Medium proximity * High geographical proximity*	0.31	0.29	0.39	0.16
	(0.36)	(0.42)	(0.41)	(0.36)
*High proximity * High geographical proximity*	-0.01	0.03	-0.40	-0.13
	(0.35)	(0.33)	(0.52)	(0.35)
Log no. of employees	-0.01	-0.01	-0.02	-0.06
	(0.12)	(0.12)	(0.12)	(0.13)
Log % of tertiary education	0.25***	0.28***	0.25***	0.26***
	(0.09)	(0.09)	(0.09)	(0.09)
R&D expenditure	0.60***	0.59***	0.64***	0.60***
	(0.12)	(0.12)	(0.12)	(0.12)
Share of foreign ownership	0.65**	0.56*	0.64**	0.66**
	(0.32)	(0.32)	(0.32)	(0.32)
Industry fixed effects	Included	Included	Included	Included
Cut 1	1.64	1.68	1.68	1.55
	(0.54)	(0.54)	(0.54)	(0.54)
Cut 2	3.10	3.17	3.15	3.03
	(0.56)	(0.56)	(0.56)	(0.56)
N	393	390	391	391
Log likelihood	-366.45	-364.89	-364.04	-363.89
Pseudo-R^2	0.14	0.14	0.14	0.14

Note: The numbers in brackets refer to standard errors of the coefficients.

*: P < 0.10, **: P < 0.05, ***: P < 0.01

The analyses provide some support for the hypothesis of a substitution-innovation mechanism, but no evidence of the presence of an overlap-innovation mechanism.[7] In particular, the combination of high non-geographical proximity and low geographical proximity has a positive coefficient in all models and is significant for cognitive, organisational, and institutional proximity. The combination of medium non-geographical proximity and low geographical proximity is also positive and significant in three of the four dimensions – cognitive, social, and institutional proximity. In these cases, firms seem to be able to bridge low geographical proximity to their partners with higher proximity in one or more of the non-geographical dimensions. However, the combination of low geographical and non-geographical proximity is also significant for both organisational and social proximity, suggesting that firms that keep a distance to their partners across several dimensions can still benefit from these partnerships in their innovation processes. Yet, the presence of at least one type of non-geographical proximity appears to be critical. Of the 77 instances of low geographical proximity, there is only one case (=1.3 percent) where non-geographical distance is present in all dimensions. Conversely, 27 out of 77 firms (=35.1 percent) with low geographical proximity to partners have medium or high proximity to their partners in all non-geographical dimensions. Looking at the whole sample of firms, there is only one out of 368 cases (=0.27 percent) where low geographical proximity is combined with low proximity in all non-geographical dimensions.

For medium geographical proximity, only two of the coefficients are statistically significant, specifically the combinations with high social proximity and with medium institutional proximity. For

[7] The results are similar when Scandinavia is treated as medium proximity, while they provide even stronger support for the compensation mechanism hypothesis when "in the same region" is treated as medium proximity. In the latter case, all combinations of high non-geographical and low geographical proximity have a significant effect, as do three combinations of medium non-geographical and low geographical proximity. Conversely, no combinations of low non-geographical and low geographical proximity are significantly associated with innovation in this specification.

high geographical proximity, none of the coefficients are significant. However, it is worth noting that the combination of high geographical and high non-geographical proximity has a negative coefficient in three of the four dimensions, indicating that too much proximity may indeed be harmful for innovation.

These results on the interactions between geographical and non-geographical proximities add important contextual qualifications to the Goldilocks principle. Overall, the Goldilocks principle only holds consistently for low geographical proximity, with medium cognitive, social, and institutional proximity being most strongly associated with product innovation. Again, organisational proximity is the exception with positive and significant effects for low and high proximity only. For medium geographical proximity, the Goldilocks principle holds most clearly for institutional proximity, whereas for all other cases the results are generally inconclusive.

5. Discussion and conclusions

This study has examined the role of proximity for innovation by considering multiple types of proximity in a holistic fashion. A dedicated survey on proximities of the most important external partners for innovation – as indicated by the CEOs and managers of the surveyed firms – offers more direct indicators of the levels of proximity than previous quantitative studies, which have tended to use indirect and rather crude measures of non-geographical proximity. This paper has also scrutinised the distribution of proximity variables rather than merely analysing mean values, positing that the types of proximity may not be independent of one another, but interrelated.

The first contribution of the paper is to provide empirical evidence to substantiate the so-called Goldilocks principle: in order to maximise the innovative capacity of networks, the partners involved should be at the 'right' distance in the cognitive, organisational, social, and institutional spectrum: 'not too close and not too far' from one another. This principle is particularly strong in the case of

Norwegian firms in the sample. The confirmation of the Goldilocks principle in the analysis can potentially address the tension of the ‘proximity paradox’ (Boschma and Frenken 2010), as collaboration with partners for innovation works best at mid-level non-geographical distances. Bivariate correlations largely support the generalised Goldilocks principle. First, having external partners is positively associated with innovativeness. Second, the highest share of new-to-market innovators can be found among those which collaborate with partners at medium levels of proximity for all non-geographical types of proximity. For geographical proximity, it is those firms that are collaborating with partners at a longer distance that are most likely to innovate and to introduce new-to-market innovation, which supports previous findings (Fitjar and Huber 2015; Fitjar and Rodríguez-Pose 2011, 2013; Kesidou and Snijders 2012). Multivariate ordinal logit regression analyses further reinforce the principle, as the strongest and most significant coefficients appear in the indicators for medium proximity: collaborating with partners at a medium level of proximity is associated with innovating at a higher rate, which is statistically significant for all types except for organisational proximity. By contrast, collaborating with partners at high proximity is not associated with significantly better innovative results relative to having no partners at all.

A second contribution of the paper is to provide a novel empirical assessment of the role of the substitution mechanism and the overlap mechanism for innovation. Here the paper goes beyond Hansen (2015) and Huber (2012a) by linking the substitution versus overlap question to innovation outcomes to test the additional hypotheses of the overlap-innovation mechanism and the substitution-innovation mechanism. There is some evidence that geographical distance can be compensated by proximity in other dimensions, which illustrates the importance of the substitution-innovation mechanism. Geographically distant partnerships combined with high levels of cognitive, organisational, and institutional proximity are positively associated with product innovation. Medium levels of cognitive, social, and institutional proximity combined with geographical distance are also positively related to innovation. Low organisational and social proximity combined with low geographical proximity also display a positive relationship with innovation. Whilst the latter result suggests that distance to partners across several dimensions can still be effective for innovation, overall the analysis indicates that at least one type of non-geographical proximity needs to be present. Low geographical proximity combined with low proximity in all non-geographical dimensions is only reported in 0.27 percent of the cases. This provides support for the theoretical perspective of a substitution mechanism where the disadvantages of high geographical distance can be overcome by proximity in at least one other dimension (Huber 2012a). The results do not support the traditional argument of the overlap-innovation mechanism (Malmberg and Maskell 2006; Saxenian 1994) that geographical proximity facilitates the development of proximity in non-geographical dimensions, which subsequently facilitates innovation. On the contrary, although not statistically significant, the combination of high geographical and high non-geographical proximities tends to be negatively associated with innovation. These results cast doubt on the widespread theoretical assumption of the overlap-innovation mechanism: geographical proximity's role of enabling other types of proximity for innovation appears to be limited. In contrast, non-geographical proximity enabling geographical distance, or geographical proximity enabling distance in other dimensions, may be more important for innovation. This is an important result which deserves further research.

Despite its novelty, several *limitations* of this study need to be considered.

First, as the research is centred on an analysis of firms' relationship to their most important external partner, it is not able to shed light on the question of what could be the optimal overall configuration of the portfolio of external partnerships for innovation. As Boschma and Frenken (2010) have argued, having a balanced mix of different relationships, combining some proximate and some distant partners, may lead to optimal outcomes, which needs to be addressed by further studies.

Second, more research is needed to clarify why certain types of proximity can be beneficial for innovation, and how the compensation mechanism operates, which requires more detailed qualitative research on the processes involved in these relationships. Desired proximity characteristics may be dependent on intended motivations of partnerships (Hansen 2014) or may vary for different innovation activities. Again, this is an issue which would deserve further attention in future research.

Third, the paper has not included an analysis of the role of temporary geographical proximity (Bathelt and Schuldt 2008; Torre 2008).

Finally, of course, this research provides an empirical snapshot and cannot shed light on the evolution of proximities over time (Boschma and Frenken 2010; Broekel 2015; Steinmo and Rasmussen 2016). We expect that, if this type of analyses becomes popularised, new surveys would allow us to add not just a time dimension, but also a much-needed geographical dimension to understanding how different types of distance affect the efficacy of innovation networks.

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