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Geographic distance between co-inventors and firm performance: The moderating roles of interfirm and cross-country collaborations

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ABSTRACT

Firms use strategic collaborations to reduce costs and increase productivity through shared technological capabilities, knowledge and resources. However, technological collaboration over geographic distance involves the risks of facing communication problems including vulnerability to the language difference, cultural issues, and political barriers. Consequently, firms engaging in technical collaborations across different locations often face higher communication (and other distance-related) costs, which in turn could affect their financial performance. This paper investigates the relationship between inventor distance and firm performance by employing panel fixed effect quantile regression techniques with interaction variables on a sample of 556 firms. The study finds empirical evidence that the geographic distance between collaborating inventors has a positive effect on firm performance. This effect is stronger in companies that engage in inventor collaborations across international borders and weaker in multi-national corporations that rely only on intra-firm inventor collaborations.

1. Introduction

In today's business world, a firm's survival relies heavily on its innovative capability. Innovation driven firms are facing ever-changing challenges and competition stemmed from the fast pace of technological progress. Technological knowledge plays a vital role in innovation and thus firms constantly need to build their knowledge base through research and development (R&D). By doing so, they may be able to devise their technological and scientific strategies and expand their innovative capabilities to emerging business areas (Deeds et al., 2000; Grant and Baden-Fuller, 2004; Powell et al., 1996; Wilden and Gudergan, 2015; Zander and Kogut, 1995). However, as pointed out by prior studies, expanding innovative capabilities to new areas is not easy. Firms prefer to search for new knowledge within their existing technological domain (Benner and Tushman, 2003; Rosenkopf and Almeida, 2003; Stuart and Podolny, 1996).

Research and development (R&D) alliance are among the most common business strategies used by firms, through joint technological collaborations, in efforts to reduce cost and increase productivity (Hagedoorn, 1993) and innovative outputs (Moaniba et al., 2019). These alliances enable firms to acquire external technical knowledge (Frankort, 2013; Frankort et al., 2012a; Gomes-Casseres et al., 2006; Mowery et al., 1996; Oxley and Wada, 2009; Rosenkopf and Almeida, 2003). Nonetheless, a number of studies have highlighted that reliance on R&D alliance may have negative consequences (Chen & Li, 1999; Deeds et al., 2000; Deeds & Hill, 1996; Kotabe & Scott Swan, 1995; Rothaermel & Deeds, 2004). For instance, firms engaging in technological collaborations may face social and political barriers due to cultural difference, geographic distance, and language; leaked knowledge to competitors through their alliances; over-reliance on costly alliances; and limited understanding on how different collaboration networks may affect their financial performance. These problems often translate into financial costs and higher R&D spending levels (Su and Moaniba, 2020), which in turn, can disrupt firm performance.

A popular research stream in the field of R&D alliance strategies focuses on the how geographic location matters in partnerships. The bulk of studies in this stream suggests that location is strongly linked to firm performance (e.g., Decarolis & Deeds, 1999; Gilbert, McDougall, & Audretsch, 2008; Kafouros, Wang, Mavroudi, Hong, & Katsikeas, 2018; Tsai, Ren, & Eisingerich, 2020). However, findings have been mixed. Some studies emphasized the importance of geographic proximity in knowledge creation and firm performance (e.g., Gilbert et al., 2008; Oerlemans & Meeus, 2005) while others point to the geographic diversity and coverage as contributors to firm performance (Driffield et al., 2008; Kafouros et al., 2018). This controversy ignites the need for studies with narrower scopes. To address such issue, this paper focuses on the geographic distance aspect of a collaboration from inventors' perspective only to examine its relationship with firm performance. In addition, little is known about how different types of

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inventor collaboration networks influence such a relationship. Prior studies have acknowledged different forms of collaboration networks such as beyond border alliances that allow firms to source knowledge (Cassiman and Veugelers, 2002; Laursen and Salter, 2006). Various papers have also indicated the importance of organizational level R&D alliances in allowing firms to acquire outside knowledge (Hagedoorn and Duysters, 2002; Rosenkopf and Almeida, 2003; Rothaermel and Deeds, 2004; Srivastava and Gnyawali, 2011; Stuart and Podolny, 1996).

Most often, inventors ignore the (geographic) distance aspect of a collaboration network when choosing their innovation partners. Instead, they base their decisions on things such as the skills of the person and how well they know them. However, as explained earlier, problems imposed by the distance between inventors can translate into costs (Su and Moaniba, 2020) and therefore it is imperative that they (i.e., inventors or the companies they work for) understand the relationship between geographic distance and firm performance. Furthermore, knowing the benefits (or consequences) of the type of collaboration network adopted and whether they can help mitigate the financial problems is also vital for an innovative firm. Knowledge of such kind can help companies formulate effective partnership and innovation strategies. Distant collaboration (especially across countries) has been increasingly popular since the advent of the internet despite involving knowledge transfer problems such as language and cultural differences, which in turn, may hinder or prevent positive outcomes (Berry, 2014; Cohen and Levinthal, 1990; Jaffe et al., 1993; Sampson, 2007; Wagner et al., 2011).

In this study, we argue that there is a strong connection between (geographic) inventor distance (referred to as collaboration distance in this paper) and firm performance, and that this link can be moderated by two different forms of collaboration networks: 1) at an organizational level (i.e. firm-level from business perspective) where inventors from one firm can either choose to collaborate among themselves (i.e. an intra-firm collaboration) or with inventors from other companies (i.e. interfirm collaboration). 2) at a country level where inventors may collaborate with other inventors from the same country or with those from other countries (i.e., a cross-country collaboration). An interfirm collaboration at the same site or across different locations. Different types of collaborations have different advantages and disadvantages – due to the heterogeneity in business environments, regulations and bureaucratic systems across firms, and the different languages, cultures and foreign policies among countries. This present study provides empirical evidence that the geographic distance between collaborating inventors has a positive effect on firm performance. This effect is stronger in companies that engage in inventor collaborations across international borders and weaker in multi-national corporations that rely only on intra-firm inventor collaborations.

The lack of knowledge on how the geographic distance between inventors can affect firm performance and how the different types of collaborations can moderate this impact is an important literature gap. Knowing the benefits and costs of different forms of inventor networks would widen our understanding of the broader concept of innovation-performance nexus, from a business perspective. The relationship between a firm's collaborative activities and its performance has inspired research interests from various disciplines. These include a large body of literature examining the impacts of strategic alliance on firm-level innovation (Ahuja, 2000; Brown and Eisenhardt, 1995; Dodgson, 1992; Duysters and Hagedoorn, 1998). Moreover, the bulk of these studies have focused on investigating the moderating effects of social factors such as culture, language, and R&D expenditure on the relationship between geographic distance, technical collaboration and organizational performance – mostly in the context of a cross-country cooperation. To our knowledge, the relationship between geographic inventor distance and firm performance has hardly been examined and that there is no previous empirical study investigating the moderating effects of interfirm and cross-country collaborations on this distance-performance relationship.

This paper contributes to the theory and literature in several ways. First, it extends the innovation strategy literature on the link between a strategic alliance and firm growth by providing empirical evidence that the geographic distance between collaborating inventors has a positive and significant effect on firm performance. Second, the study shows that this effect can be moderating by different types of collaboration networks. For instance, both interfirm and cross-country collaborations have significant positive moderating effects on the relationship between geographic distance and firm profitability. Third, a novel approach to constructing a firm-level indicator of collaboration distance per yearly basis is introduced. This indicator is computed based on the longitudes and latitudes of the cities of inventors and patent data.

The remainder of the paper is structured as follows. The next section presents the literature review, background theory, and our hypotheses. Then, the methodology and the results of our empirical analysis hypotheses testing are provided and discussed. Finally, the managerial implications, limitations of this study, and recommendations for future research are presented.

2. Theoretical Background

2.1. R&D strategies and collaboration networks

A firm's effort to integrate strategic collaboration and innovation improvement strategies can lead to its successful performance (Penner-Hahn and Shaver, 2005). R&D spending is instrumental in strategic collaboration to ensure knowledge acquisition and significant development to an organization's innovative capability (Alexy et al., 2013). Newly developed knowledge is key to achieving a firm's competitive advantage and therefore should be legally protected through patenting (Ceccagnoli, 2009; Shane, 2001). Previous studies indicate that R&D spending and patenting activities have a positive relationship (Nicholls-Nixon and Woo, 2003). Through R&D, firms are able to develop new knowledge by screening, acquiring and recombination of external knowledge, which in turn, help them create not only patentable but also high-value inventions (Kaplan and Vakili, 2015; Nicholls-Nixon and Woo, 2003; Somaya et al., 2007).

Distant collaboration has drawn considerable attention and questions relating to whether it can actually translate acquired knowledge into immense benefits. Knowledge acquired through distant networks is perceived to have higher commercial value, degree of diversity, and novelty (Capaldo and Messeni Petruzzelli, 2015). For instance, in a typical university-firm network, geographical distance has been shown to have a positive influence on innovation performance (Petruzzelli, 2011). Knowledge transfer and recombination across geographic regions have also been observed to have positive impacts on the quality of innovation (Moaniba et al., 2018). Furthermore, knowledge not available locally are often acquired from other regions via technological collaboration (Ahuja and Katila, 2004).

Combining internal knowledge with a wider range of external knowledge sources through R&D collaborations across geographical distance increase the chances of productivity (Ahuja, 2000; Sampson, 2007). This is consistent with the idea that the success of collaboration networks is affected by individuals and countries involved (Glänzel and Schubert, 2004). This, in turn, can affect the outputs of knowledge re-combinations resulting from internal and external sources. Despite the time consuming and high costs involved in long-distance collaborations, firms still continuingly engage in them. Clearly, this implies that the benefits of long-distance collaboration must outweigh the costs, and therefore means higher returns (Pérez-Luño and Valle-Cabrera, 2011). Based on the above observations, we hypothesize that:

Hypothesis 1. The geographic distance between collaborating inventors has a positive effect on firm profitability.

2.2. The moderating roles of an interfirm level and cross-country level collaborations

Various research has indicated the positive role of organizational level R&D alliances in allowing firms to acquire outside knowledge (Hagedoorn and Duysters, 2002; Rosenkopf and Almeida, 2003; Rothaermel and Deeds, 2004; Srivastava and Gnyawali, 2011;

Stuart and Podolny, 1996). Firm-level collaborations allow companies to effectively integrate knowledge and achieve competitive advantages (Berry, 2014). There are a number of known benefits of an organizational level collaboration. These include reduced transaction costs, increased environmental adaptation, and improved competitive advantage (Bae and Gargiulo, 2004)), as well as getting exposed to a wider range of knowledge sources and experience not only through entering new partnership alliances but also through the process of closing old partnerships (Ahuja, 2000; Cohen and Caner, 2016; Vasudeva et al., 2012). In addition, firms engaged more in firm-to-firm collaboration networks may likely gain benefits, in both local and international settings, by increasing their technological negotiation power with potential collaborators, help firms consolidate their acceptance in cooperation networks, and enhance their domestic and overseas market power (Pérez-Luño and Valle-Cabrera, 2011; Shane, 2001; Somaya, 2012). Nevertheless, firm-level collaboration can be hindered by tight company regulations, slow bureaucratic organizational processes, and institutional culture (Blind et al., 2006; Lu and Beamish, 2004; Zahra and Bogner, 2000). These arguments lead us to hypothesize that:

Hypothesis 2. The effect of the geographic distance between collaborating inventors on firm profitability is stronger in companies that engage in interfirm (i.e., firm-to-firm) collaborations than in those companies that do not.

Long-distance collaboration, especially across countries, often involves higher cost and political barriers. This occurs as knowledge transfer will, under some circumstances, require face-to-face communication. In addition, due to political barriers, language and cultural differences, knowledge acquired from other countries can create a high level of dispersion and inefficiency (Berry, 2014). These problems can, in turn, lead to coordination issues. Consequently, firms would need to come up with costly improvements to their coordination strategies and ways to synchronize internal and external knowledge combination so that to optimize outputs (Foss et al., 2013). Knowledge sharing with foreign partner firms can also result in knowledge leakage to foreign competitors (Oviatt and McDougall, 2005). Furthermore, knowledge acquired from international partners can be difficult to understand and apply (Sampson, 2007), leading to less effective absorptive capacity (Cohen and Levinthal, 1990), and loss of trust or motivations for future collaborations with existing partners (Berry, 2014). These observations suggest the following hypothesis:

Hypothesis 3. The effect of geographic distance between collaborating inventors on firm profitability is weaker in companies that engage in international (i.e., cross-country) collaborations than in those companies that do not.

When analyzing the relationship between inventor collaboration and organizational performance, and the effects of the distinctive characteristics of collaboration network on such relationship, it is important to recognize the different types of technical collaboration. It has been acknowledged that factors such as geography, institutions, politics, and language play important roles in collaborations (J. Davidson Frame and Mark P. Carpenter, 1979). This implies that the success of a collaboration is highly dependent on the organizational settings and regulations, and foreign policies of countries involved. For this reason, we argue that a collaboration across firms has advantages and disadvantage that are different from those of a cross-country collaboration.

As summarized in our theoretical framework in Fig. 1, we propose that the geographic distance between collaborating inventors has a positive effect on firm performance and that this effect can be moderated by two types of collaboration networks discussed previously – interfirm and cross-country collaborations. Note, based on literature review, we anticipate the effect of geographic distance on firm performance to be positively influenced by interfirm collaboration, and negatively by cross-country collaboration (where not only social impediments are common such as language difference but also economic and political barriers).

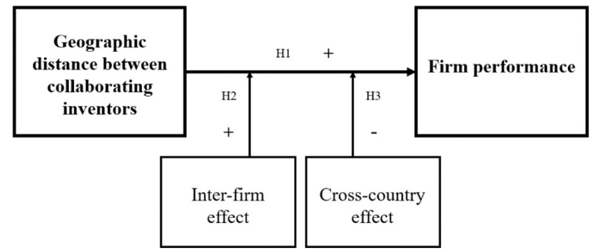


Fig. 1. Theoretical framework.

3. Data

3.1. Data sources

This study utilized firm financial data and USPTO patent data to analyze the relation between inventor geographic distance and firm performance. Our USPTO patent data are obtained from the PATSTAT database (European Patent Office, 2017) and firm financial data are gathered from the EU Economics of Industrial Research & Innovation scoreboard maintained by the European Commission's Joint Research Centre (IRI Team, 2017). The scoreboard provides a worldwide ranking of companies with highly annual R&D investments since 2004. It contains R&D expenditure and other financial data for each of the companies in the ranking. In 2016, there a total of 2,500 companies listed on the scoreboard. These top 2,500 ranked companies are initially targeted by this study. Unfortunately, not all of them made it to the scoreboard every year between 2004 and 2016 (i.e., during the 13-year period), and also not all of them were granted patents by USPTO (or applied for patents to USPTO) every single year between 2004 and 2016. The ones that did not make the IRI ranking and have no granted patents in more than two years during the 13-year period (which accounts for 1,946 companies) are dropped. This leaves our final dataset with 556 firms. Therefore, in total, we have 7228 observations in our panel dataset – i.e. 556 firm observations x 13 years (from 2004 to 2016).

In addition, it is also important to note the following: 1) The remaining 556 firms in our sample have a combined total of 1,067,405 granted patents between the year 2004 and 2016, which is quite a significant number for the type of panel regression analysis we intend to pursue. 2) our analysis uses the application dates of USPTO patents. This said, all USPTO patent records obtained from PATSTAT are on published patents. Patent applications rejected or withdrawn prior to publication cannot be observed and therefore not considered in this study. 3) Although all financial variables required in our regression analysis can be observed directly from the data available in the IRI database (e.g. the number of employees and profitability ratios for firms in each year), the technological-related variables we need on the other hand (e.g. firm originality index and firm patent family size) have to be calculated from the data compiled from the 1,067,405 patent records.

3.2. Dependent variable – Firm profitability

Our primary goal in this study is to explore the effect of the geographic distance between collaborating inventors on firm performance and thus employ firm profitability as our proxy for firm performance. Firm profitability is defined and computed as the ratio of a firm's operating profit to its net sales in a given year (IRI Team, 2017). It has been suggested and used a number of times in the past as a good indicator of the outcome of new technology commercialization (Frankort et al., 2012b). Moreover, it has also been argued to reflect the competitive environment a firm faces (Falk, 2004).

Profitability values in our sample range from -10,400 to 169.42. Note, a negative value indicates that a firm incurred a negative profit (or a loss) in a given year. Out of the 7,228 observations, only 4 are less than -1,000. The majority of the values, though, lies between -100 and 100 (which accounts

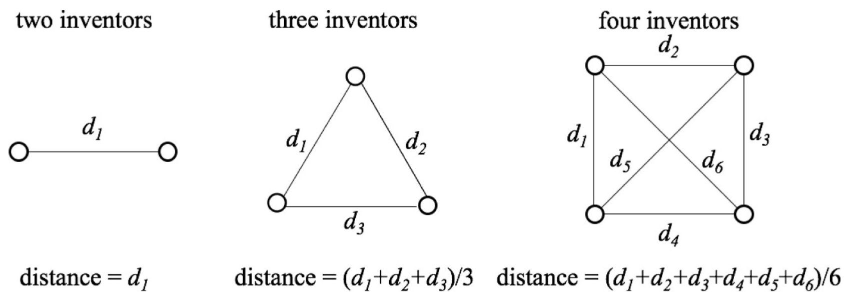


Fig. 2. The Geographic distance between inventors

for 99.3% of the observations). The average firm profitability for the 556 firms in our sample fluctuates significantly over the 13-year period. As shown in Fig. A1 in the Appendix, the average profitability reaches the lowest value of close to -10 and the highest value of just over 10. Not surprisingly, the averages are mostly lower and unstable between 2007 and 2010 probably due to the global great recession and its long-lasting effects in the late 2000s (Grusky et al., 2011). Despite these fluctuations, it is clear that the average seems to be generally increasing over the period.

3.3. Independent variable – Collaboration distance

In order to measure and compare the geographic distances between co-inventers across firms, we construct a "collaboration distance" indicator variable. This variable is simply the average of a firm's average geographic distance (in 1000 km) between the cities of collaborating inventors per its patented invention. The collaboration distance for a given firm is calculated for each year. The calculation involves two steps.

In the first step, we follow Reuer and Lahiri's (2013) approach to compute the "geographic distance" between the cities of each pair of inventors in a patent. The formula for this calculation is as follows:

$$\textit{geographic distance} = r \times \textit{arccos}\,[\sin(lat_i) \times \sin(lat_j) + \cos(lat_i) \times \cos(lat_j) \times \cos(lon_j - long_i)]$$

where r denotes the radius of the earth in kilometers (i.e. r = 6,377 km), i indicates the first inventor involved, and j refers to partner inventor. *lat* and *long* are the latitude and longitude values, respectively, of inventor cities converted into radians by means of a division by 180/π. The cities of the inventors are provided in the USPTO patent documents. Note, if a patent has more than two inventors then the average geographic distance between every pair is used. To clarify this, consider the following scenarios in Fig. 2. In the first scenario where there are two inventors collaborating, the geographic distance is d_1. In the second scenario where there are three inventors collaborating in a patented invention, the geographic distance is calculated as $(d_1+d_2+d_3)/3$ – i.e. the average of the three distances. In the third scenario, the geographic distance is calculated as $(d_1+d_2+d_3+d_4+d_5+d_6)/6$. A patent with only one inventor is treated as a non-collaborated patent. Since the focus of this study is on collaboration, all non-collaborated patents are not considered in this study. Specifically, with a significant number of non-collaborated patents in our original sample, including them in the analysis can lead to biased results because they have null (or undefined) geographic distance values.

The geographic distance formula for a patent with more than one inventor can be generally expressed as follows, where i is the number of inventors in a patent and d_j is the geographic distance between the j^{th} pair of inventors.

$$\text{Geographic distance}= \frac{\sum_{j=1}^{i(i-1)/2} d_j}{i(i-1)/2} \text{for } i > 1;$$

In the second step, we calculate values of our collaboration distance variable for each firm in our sample, for each given year, by taking the average of the geographic distance values (per patent computed in the previous step). It is important to know that the formula in the first step calculates the geographic distance for one patent. Therefore, a firm with only one patent is assigned the same collaboration distance variable value as the geographic distance of that single patent. For a firm with more than one patent, the average geographic distance of its patents is taken as its collaboration distance. For example, if firm A has four patents in 2010 and the geographic distance between inventors in each of the four patents (calculated in the first step) are 20, 40, 40, and 60 (in km), then their average, which is 40 km i.e. (20 + 40 + 40 + 60)/4 (in km), is taken as the collaboration distance for firm A in the year 2010.

The values of our collaboration distance variable range from 0 to 16,010 km, where zero indicates that the collaborating inventors are located in the same city while 16,010 km means that they are roughly "halfway around the world" from each other[1]. Nevertheless, 99.67% of the 7228 observations have collaboration distance values between 0 and 5,000 km whereas the rest (= 16 observations) are between 6,000 km and 16,010 km (of which only one has a collaboration distance value that exceeds 10,000 km. The annual average collaboration distance for the 556 firms in our sample exhibits a steady and gradual increasing trend over the 13-year period. This pattern indicates the increase in popularity of distant collaboration during the period, probably due to the rapid globalization and technological breakthroughs that have helped reduce communication barriers and transportation costs. Consequently, longer-distance collaborations have become easier than before. For instance, long-distance social and institutional collaborative networks have been known to facilitate knowledge exchange (Autant-Bernard et al., 2007; Knoben, 2009).

3.4. Control variables

A number of variables have been highlighted in literature as determinants of firm performance. Some of these variables are selected as control variables in this study in order to improve estimation efficiency and prevent omission bias. These controls are:

3.4.1. Employees

The number of employees in an organization (or firm in our case) has been widely used in previous literature as the proxy for the size of a firm (Petruzzelli, 2011; Rangus and Slavec, 2017; Tanriverdi and Venkatraman, 2005). In this study, we control for the different firm sizes by using the number of employees. To ensure the values of this variables is within a reasonable range with the dependent variable, all values are divided by 1000 (i.e. its values are in 1000 units).

3.4.2. R&D intensity

R&D intensity has been used so many times before in previous studies as a measure of a firm's technological capability or absorptive capacity (Coombs and Bierly, 2006; Hsu et al., 2015), and has been shown to strongly influence firm performance. We therefore also control for the different R&D intensity levels of firms by including this as one of our explanatory variables.

[1] Since the earth's circumference is 40,075 km and therefore a halfway distance across the world is 20,000 km.

3.4.3. Originality index

To control for the diversity of technologies in a firm, we use the originality index. A firm's originality index is adapted from the originality index proposed by Trajtenberg, Henderson, and Jaffe (1997) to indicate the originality of a patented technology. The originality index of a firm is expressed mathematically as follows:

$$Originality\ index_i = 1 - \sum_{j}^{n} SB_{ijk}^2$$

where SB_{ijk} is the share of previous patents cited by patent i that belong to patent class j out of $n = 35$ patent classes, where patent i is from firm k. The originality index ranges from 0 to 1. If a patent cites a number of prior patents belonging to the same technological field, the originality index is low. If most prior patents belong to many technological fields, the originality index is high. A higher originality index indicates that the patent in question is more original and not directly derived from prior patents. A four-level IPC classification was used to define technological fields. For patents assigned to multiple IPCs, the first and primary IPC is used. The originality index has been recognized as a good indicator of the diversity of technologies. Technological diversity is known to influence performance (Lu and Beamish, 2004).

3.4.4. Patent count

Previous studies have proposed that patent count is a good measure of innovation (Jaffe et al., 1993; Jaffe and Trajtenberg, 1999). This present study adopts patent count as a proxy and means of control for the differences in firms' innovation capabilities. It is simply the total number of USPTO patents granted to a firm in a given year. The more patents granted to a firm in a given year means the more innovative capable a firm is.

3.4.5. Patent family size

To control for the differences in the quality of firm innovations, we construct a patents family size variable for each firm. The variable records the average number of a firm's patents family size per given year (using Inpadoc patent family). Patents family size has been proposed and used a lot to indicate the value of a patented invention (Harhoff et al., 2003).

Another known factor influencing firm performance that could be also added as a control variable is the patent forward citation count (Deng et al., 1999). However, forward citation count can cause truncation problems as patents that have been published longer tend to get higher citations than newer patents. The commonly used way around this is to use a restricted citation period such as within 5 years or 10 years after the patents were published. Unfortunately, because our data covers a short period (13 years only), excluding a 5-year or 10-year citation window will leave us with limited data to analyze. For this particular reason, forward citation count is not included as a control in this study.

3.4.6. Cultural distance

We also control for cultural diversity by using the index that is based on six dimensions –Individualism, Power Distance, Masculinity, Uncertainty Avoidance, Long-term Orientation, Indulgence (Geert, 2015). This measure has been used in previous studies as a proxy for cultural differences between firms involved in collaborations (e.g., Ardito, Petruzzelli, Pascucci, & Peruffo, 2019; Capaldo & Petruzzelli, 2014; Elia, Messeni Petruzzelli, & Piscitello, 2019; Petruzzelli, 2008). It is calculated as follows:

$$CD - partner = \sum_{l=1}^{6} \frac{(I_{l,j} - I_{l,s})^2/\mathrm{V}_l}{6},$$

where s is the country in which the firm is located, j is the country in which the j_{th} partner is located, $I_{l,\ j}$ is the score for the $\mathrm{l_{th}}$ cultural dimension, and V_l is the variance in the $\mathrm{l_{th}}$ cultural dimension.

3.5. Moderator variables

As mentioned previously, apart from investigating the effect of geographic distance between inventors on firm performance, we are also interested in exploring the moderating roles of two types of collaboration networks – interfirm collaboration network and cross-country collaboration network.

3.5.1. Interfirm collaboration

Interfirm collaboration is defined in this study as a collaboration between inventors from different companies whereas a cross-country collaboration is defined as a collaboration between inventors from different countries. Inventor collaboration refers to a technical partnership between inventors in which they collaborate and work together on an invention.

In patent records, the registered name of a firm that was granted ownership of a patent is labeled as assignee. An inventor listed under a given assignee indicates that the inventor belongs to that assignee (i.e. firm). The number of assignees in a patent indicates the number of firms collaborating. A patent with zero number of assignees implies that the inventor of such patent is an individual that does not belong to any firm. Since this is a firm-level study, all patents with zero number of assignees are not considered. A patent with a number of assignee = 1 shows that the inventor (or inventors if the patent has more than 1 inventor) belongs to one company.

In this study, we employ a dichotomous dummy variable *interfirm* as our first moderator variable, to indicate whether the collaboration between inventors in a patent is between different firms or not. A firm with an average number of assignees (per patent) of more than 1, in a given year, is labeled as an interfirm collaborator in that year[2]. On the other hand, a firm with an average assignee number of at most 1 in a given year is considered a non-interfirm collaborator in such year (occurs if collaborating inventors are from the same firm). Relatedly, our moderator variable, interfirm, is assigned a value of 1 if a firm is an interfirm collaborator or 0 if it a non-interfirm collaborator in that specified year.

3.5.2. Cross-country collaboration

Our second moderator variable is *cross-country*. Cross-country collaboration in this study refers to a collaboration between inventors from multiple countries (i.e., more than 1 average assignee country)[3]. The cross-country moderator variable is again a dichotomous variable having a value of 1 if a firm engaged in a cross-country collaboration, otherwise 0 (if not). In principle, a firm with a patent assignee country count of more than one is considered engaged in cross-country collaboration, whereas a firm with a patent assignee country count of less than 1 is considered engaged in a non-cross-country collaboration. Overall, the number of assignee countries in our sample ranges between 1 and 2 (see Table A1 in the Appendix).

Table 1 and 2 provide statistical summaries of our main variables – grouped by our moderator variables. As shown in Table 1, the mean profitability value for firms engaged in interfirm collaboration is lower than the mean for those that did not engage in non-interfirm collaborations (see Profitability column in Table 1). Note, although the number of assignees ranges from 1 to 4 as shown in Table A1 in the Appendix, there are only two observations that fall between 3 and 4. Specifically, out of the 7,145 firm observations for the Assignee (count) variable, only 1 firm has a number of assignees = 3 in a given year and 1 firm has a number of assignees = 4 in a given year. The remaining 7,143 observations are between 1 and 2. In contrast, the mean profitability value for firms engaged in cross-country collaboration is lower than the mean of those that did not (see Profitability

[2] We use the average number of assignees per patent because firms can have more than one patent in a given year. Taking the average can result in a non-integer number of assignees.

[3] Again, we use the average number of assignee countries per patent because firms can have more than one patent in a given year. Using the average can result in firms with a non-integer number of assignee countries.

column in Table 2).

Our main independent variable, collaboration distance (written as Distance in Table 1 and 2), also exhibits similar patterns over the years and across firms. Interestingly, the mean collaboration distance is higher in firms that did not engage in an interfirm collaboration as compared with the mean for firms that did engage in interfirm collaboration. On the other hand, the average collaboration distance is slightly higher for firms that engaged in cross-country collaboration as opposed to those that did not. Further statistical descriptions of our main variables are provided in Table A1 in the Appendix.

The kernel densities of collaboration distance for each moderator variable are reported in Fig. 3. As depicted in the two graphs, the density of firms engaged in an interfirm collaboration tends to be higher than that of firms engaged in a non-interfirm collaboration at lower values of collaboration distance (roughly below 2000 km in the first plot), whereas cross-country collaborating firms have higher density levels for most values of collaboration distance – except the lowest and highest values of distance (roughly below 500 km and more than 3,000 km, respectively). These density patterns suggest that the adoption of interfirm collaboration by firms seems to decline as the geographic distance between inventor partners gets relatively large. In other words, the majority of inventors tend to prefer collaborating within their company (instead of with inventors from other firms) as the distance gets larger – e.g. a long-distance inventor collaboration across different countries between employees of a multi-national corporation. This choice of a partnership is perhaps related to the high costs of collaborating with other firms' inventors as the distance gets larger.

In contrast, the second graph suggests that inter-country collaboration is common where the geographic distance between inventors is in mid-range (in this case, roughly between 500 km and 3000 km). Inventors preferring to collaborate within their country is obviously reasonable when the distance is short (e.g. approximately less than 500 km in the second plot in Fig. 3). However, the density level for cross-country collaboration tends to drop slightly below the levels of non-cross-country collaboration as distance exceeds 3000 km. This implies that inventors, though a very small number as indicated by the low-density levels, seems to favor local partners when the distance is relatively high. This observed pattern could perhaps highlight another interesting insight on how inventors perceive cross-country collaboration as too costly for them at this point.

4. Methodology

Given the increasing trend of firm profitability, reflected by the averages in Fig. 1A in the Appendix (though with some fluctuations), questions on what causes it and why could easily arise. Could it be associated with the increasing pattern of collaboration distance (see average distances in Fig. A2 in the Appendix)? If yes, can this relationship be moderated by different types of collaborations? These kinds of questions can be answered by testing our hypotheses 1-3 described in Section 2. To do this, an estimation approach is devised. This estimation analysis involves two steps. First, we examine the effect of geographic distance between collaborating inventors on firm profitability using regressions. Second, we use interaction variables to investigate the moderating roles of: 1) interfirm collaborations, and 2) inter-country collaborations. This interaction variable approach has been commonly employed in analyzing the moderating effects of certain factors on a relationship between the outcome variable and the primary independent variable.

4.1. The relationship between collaboration distance and firm profitability

Our primary goal in the first step of our estimation analysis is to explore the relationship between the geographic distance between inventors and firm profitability. To do this, we develop a regression model that relates our main variable of interest, collaboration distance (as well as some control variables) to firm profitability. Our baseline specification model takes this form:

$$pft_{i,t} = \beta coldis_{i,t-1} + \lambda \mathrm{rdi}_{i,t-1} + \delta \mathrm{emp}_{i,t-1} + \gamma \mathrm{pat}_{i,t-1} + \varphi \mathrm{ori}_{i,t-1} + \pi \mathrm{fam}_{i,t-1} + \beta culdis_{i,t-1} + \mathrm{d_t} + \epsilon_{i,t} \quad (1)$$

where $pft_{i,\,t}$ indicates the profitability of a firm i in year t and $dis_{i,t-1}$ denotes the average geographic distance (in 1000 km) between inventors (in firm i) with their partners at year t-1. The parameter β is used to test hypothesis H1 described in Section 2.1. Five control variables (all in year t-1) are also added to the equation to control for other known drivers of profitability discussed in Subsection 3.4. These controls are: $\mathrm{rdi}_{i,t-1}$ which indicates the level of R&D intensity in a firm, and $\mathrm{emp}_{i,t-1}$ which stands for the number of firm employees. Both these variables are added to control for the possible heterogeneity in firm size and investment effects. $\mathrm{pat}_{i,t-1}$ denotes the total number of patents per firm, $\mathrm{ori}_{i,t-1}$ indicates a firm's originality index which is used as a proxy for the diversity of technologies for a firm, and $\mathrm{fam}_{i,t-1}$ stands for the average firm patent family size – used as a proxy for a firm's patent value and effort to protect its inventions. d_t is added to control for year fixed effects, and $\epsilon_{i,t}$ is the error term. Note, in this specification, we relate all 1-year lagged explanatory variables since we are more interested to see the effects of previous year's R&D, labor and inventions – knowing that they take time to generate returns or revenues. To ensure that multicollinearity[4] is not an issue between our explanatory variables in the specified model, a pairwise correlation test is conducted. The result, reported in Table A2 in the Appendix, shows no sign of major correlation problems between all explanatory variables in this model.

Next, we extend the analysis to explore the possible moderating roles of two types of collaborations discussed in Section 2.2, and test hypotheses H2 and H3. We devise two more regression models, based on the baseline specification model in Equation 1, in order to estimate the moderating effect of each of the two types of collaborations – interfirm collaboration and cross-country collaboration.

4.1.1. The moderating role of interfirm collaboration

To investigate the moderating role of inventor collaboration between different firms (i.e. interfirm collaboration), we use a dichotomous dummy variable. The dummy has a value of 1 if the average number of assignees per firm patent (in a given year) is more than 1, otherwise 0. Assignees in patent records are the registered names of companies granted ownership of the patents. Hence a value of 1 indicates more than one companies involved – i.e. interfirm inventor collaboration. To capture the moderating effect of interfirm collaborations, we develop a regression model that takes this form:

$$pft_{i,t} = \beta dis_{i,t-1} + \delta interfirm_{i,t-1} + \varphi (dis\ x\ interfirm)_{i,t-1} + \lambda cont_{i,t-1} + \mathrm{d_t} + \epsilon_{i,t} \quad (2)$$

where all variables are the same as in Equation 1 ($pft_{i,\,t}$, $dis_{i,t-1}$ and the same list of control variables represented by $\lambda cont_{i,t-1}$). The only difference is the two additional independent variables. These two are: the moderator variable $interfirm_{i,t-1}$ is a dichotomous dummy indicating whether or not a firm is engaging in a collaborated invention with other firms and $(dis\ x\ interfirm)_{i,t-1}$ is its interaction with the collaboration distance variable. This interaction term is required to test hypothesis H2 (see Section 2.2).

4.1.2. The moderating role of cross-country collaboration

Next, we employ the number of assignee countries involved per average firm patent as our indicator for cross-country collaboration. This is reflected in our next regression model expressed below:

$$pft_{i,t} = \beta dis_{i,t-1} + \delta ctry_{i,t-1} + \varphi (dis\ x\ ctry)_{i,t-1} + \lambda cont_{i,t-1} + \mathrm{d_t} + \epsilon_{i,t} \quad (3)$$

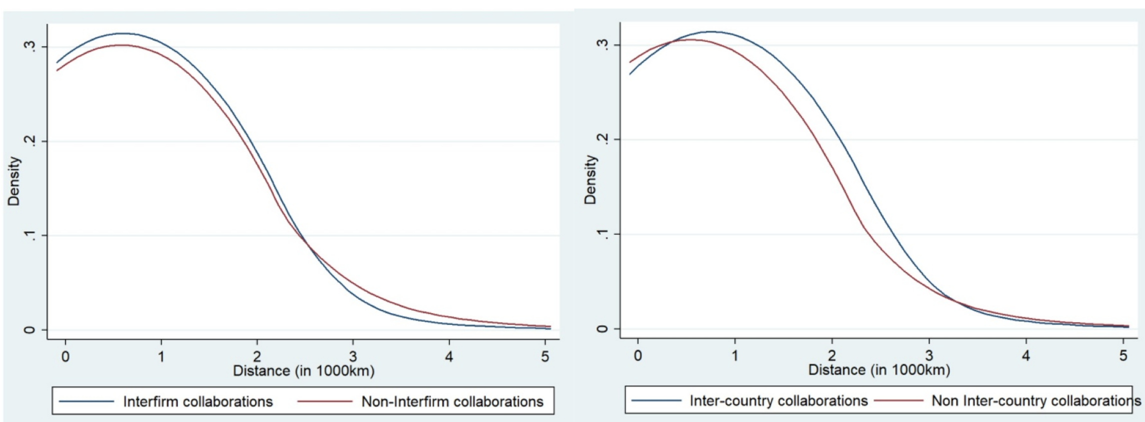
[4] Multicollinearity is a condition where two or more of the independent variables in a model are highly correlated to each other. This problem violates one important assumption of most linear regression models including quantile regression and thus can lead to biased or inconsistent results.

Table 1
Statistics comparison for main variables between interfirm collaborators and non-interfirm collaborators.

Interfirm	Obs.	Profitability Mean	R&D intensity Mean	Employees Mean	Distance Mean	Patents Mean	Originality Mean	Family size Mean
		(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)
No	3,792	5.354	10.846	23.042	0.704	65.624	0.431	12.381
		(85.108)	(72.379)	(35.357)	(0.88)	(175.144)	(0.155)	(25.559)
Yes	2,880	4.698	9.347	62.084	0.621	286.205	0.386	11.958
		(195.634)	(118.168)	(81.224)	(0.608)	(554.935)	(0.112)	(21.793)

Table 2
Statistics comparison for main variables between domestic collaborators and cross-country collaborators.

Cross-country	Obs.	Profitability Mean	R&D intensity Mean	Employees Mean	Distance Mean	Patents Mean	Originality Mean	Family size Mean
		(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)	(Std. Dev)
No	5,146	4.034	10.731	28.38	0.639	90.006	0.417	11.959
		(162.541)	(107.712)	(44.873)	(0.808)	(212.591)	(0.148)	(24.64)
Yes	1,526	8.567	8.406	78.723	0.764	399.704	0.392	13.005
		(33.333)	(15.522)	(91.92)	(0.644)	(695.235)	(0.106)	(21.718)



Note: The densities for the very few observations with distance values of more than 5000 km are way too close to zero therefore not shown in the two graphs

Fig. 3. Kernel density of Distance.
Note: The densities for the very few observations with distance values of more than 5000 km are way too close to zero therefore not shown in the two graphs

where $pft_{i,\ t}$ and $dis_{i,t-1}$ again denote the dependent variable (profitability) and our main independent variable of interest (collaboration distance), respectively. Similarly, $\lambda cont_{i,t-1}$ represents the same list of control variables in Equation 1. The moderator variable in this model is denoted by $ctry_{i,t-1}$ and the interaction term by $(dis\ x\ ctry)_{i,t-1}$. The moderator variable in this equation is again a dichotomous dummy indicating whether firm *i* is engaged in any cross-country collaborated invention in year *t-1*. Specifically, a value of 1 indicates that the average number of patent assignee countries for a firm is greater than 1 (meaning that more than one country is involved, i.e. a cross-country collaboration). The interaction term is important to test hypothesis H3 (described in Section 2.2).

Note that a single equation could have been used to test both hypotheses at the same time by inserting both moderator variables and interaction terms in the equation. Unfortunately, the moderator variables and interaction terms are highly correlated (see Table A2 in the Appendix) – especially between $(dis\ x\ interfirm)_{i,t-1}$ and $(dis\ x\ ctry)_{i,t-1}$. A high correlation between independent variables can create a multicollinearity problem, and in turn, can cause erratic or unreliable results. Multicollinearity leads to inflated standard deviations or changes in signs of the coefficients which is a serious problem in hypothesis testing (Goldstein, 1993).

4.2. Estimation method selection

In order to estimate the relationship between collaboration distance and firm profitability, we apply quantile regression. The selection of this estimation method is based on two key factors. First, the huge range of profitability values observed in our sample data, which ranges from negative -10,400 to 169.418 shows that firms in our sample are not performing equally or closely (even with the -100 to 100 range where the majority of the observations lie, i.e. 99.3% of the observations), and therefore applying the standard regression technique such as ordinary least squares (OLS) might not give us interesting results or implications. These conventional regression methods produce estimates for an average firm whereas in our case, it would be more interesting to see the estimates at different quantiles e.g. for firms with lower levels of profitability and for those with higher profitability levels – given the diverse range of profitability values. In this way, we would be able to compare the effects of collaboration distance on firm performance between these different groups of firms. More statistical details on how profitability values are distributed across the 10 quantile groups are provided in Table A3 in the Appendix.

Second, the presence of heteroskedasticity in our data provides further support for the use of a quantile regression. Heteroskedasticity is a condition in which the variance of the error terms differs across observations. Fig. 4 shows the plotted variances of the error terms against the linear predicted values of profitability for our three models discussed in the previous subsection (i.e. Equation 1, 2 and 3). As depicted in Fig. 4, the variance in each of the plots does not remain constant (or roughly constant) but rather increases with higher values of the predicted firm profitability. Therefore, the plots clearly provide evidence of the presence of heteroskedasticity in our data. Heteroskedasticity violates one of the important assumptions of standard linear regressions such as OLS (which assumes constant variance of the error terms across observations). Although there are known remedies to problems associated with heteroskedasticity, such as correcting the biased standard errors produced by OLS, its presence justifies the fact that firms in our sample are performing diversely different and therefore quantile regression is more appropriate for our analysis.

The quantile regression estimator was originally designed for a cross-sectional analysis (Koenker and Bassett, 1978). Over the years, the theoretical developments and use of quantile regression have emerged for panel data (Koenker, 2004; Canay, 2011; Galvao, 2011). One of the major issues with panel analysis is the unobserved time-invariant panel heterogeneity known as fixed effects. For instance, some firms with stronger ties due to past successful collaborations may have advantages over others. This kind of heterogeneity in firms is often hard to observe or measure. Ignoring to control firm fixed effects can lead to biased results and therefore it is important that we should deal with them accordingly. Our panel quantile regression approach follows previous studies (e.g., Canay, 2011; Coad, Segarra, & Teruel, 2016). The procedure involves transforming the dependent variable by removing the firm fixed effects. This transformation is done by, initially estimating the unobserved firm fixed effects in each of our three equations (in the previous subsection) using OLS (with fixed effect), then subtract them from the original values of the dependent variable. The usual quantile regression for cross-sectional data is then applied to estimate the three equations with the transformed dependent variable.

5. Results

This section presents our quantile regression results in three parts. First, we discuss the quantile results for our first model in Equation 1 showing the relationship between collaboration distance and firm performance. Second, we report and discuss the quantile estimation results for our moderating effects analysis for the two regression models (in Equation 2 and 3). Third, we discuss results of our robustness analysis.

5.1. The collaboration distance-firm performance relationship

Table 3 reports our results for Equation 1 for the quantiles $\Theta = 0.1$, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9. As shown in the table, the coefficients of our main independent variable of interest, collaboration distance, are all significant and positive. These results suggest that there is a positive effect of the geographic distance between collaborating inventors on firm profitability. This finding supports our first hypothesis H1, which states that firms engaged in longer distance collaborations tend to outperform others, and is consistent with most previous studies' findings (e.g., Petruzzelli, 2011; Capaldo & Messeni Petruzzelli, 2015). Another important thing to note from these results is the overall increasing pattern of the coefficient of collaboration distance across the quantiles – although it fluctuates a bit. This pattern indicates that the effect of geographic distance on firm performance is generally lower in companies that have lower profitability ratios whereas highly profitable firms tend to get a higher geographic distance effect on their performance.

5.2. The moderating effects of interfirm and cross-country collaborations

Next, we present our panel quantile regression results for our second and third equations in Table 4 and 5, respectively. Our main variables of interest are the interaction terms. These terms are designed to capture the moderating effects of both the types of inventor collaborations, interfirm and cross-country, on the relationship between collaboration distance and firm performance (found in the previous analysis).

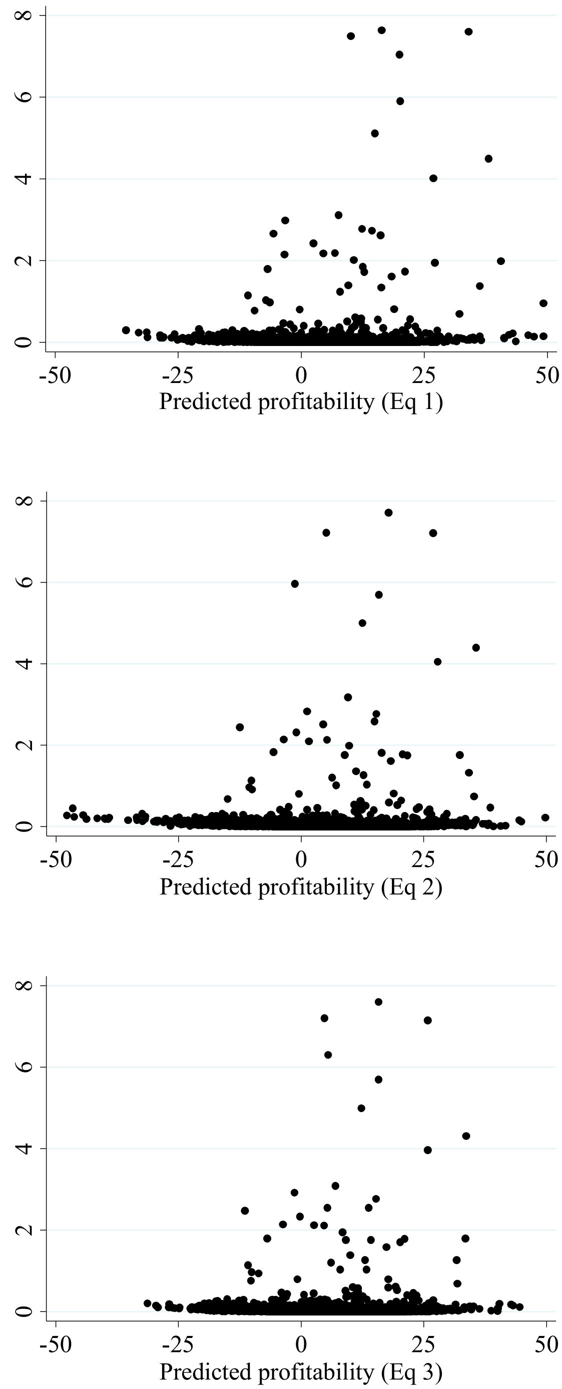


Fig. 4. Residual plots across predicted profitability values from Equation 1, 2 and 3.

We found the coefficient of our first moderator variable (i.e., Coll. Distance x Interfirm) in Table 4 to be significant and positive for all quantiles. This result suggests that firms engaging in inventor collaborations will get higher profitability levels if their partners are from other firms, as opposed to those from the same firm. This finding supports our second hypothesis H2 that states that the link between collaboration distance and firm performance is stronger in companies that engage interfirm collaboration networks than in those companies that do not. The other important thing to note is that the coefficient of our interaction term seems to increase, in general, with the quantiles. This pattern suggests that the moderating effect of interfirm collaboration is higher in firms that are highly profitable and lower in those that are less profitable. On the other hand, the coefficient

Table 3
Quantile regression results for Model 1 in Equation 1 (Dependent variable = Firm Profitability).

	Lag	10%	20%	30%	40%	50%	60%	70%	80%	90%
Coll. Distance	t-1	1.26*	2.06***	2.10***	2.26***	2.37***	2.69***	2.69***	2.63***	3.32***
		(2.44)	(9.94)	(10.11)	(14.59)	(22.25)	(24.77)	(12.81)	(12.06)	(9.60)
R&D intensity	t-1	-0.40***	-0.32***	-0.04***	0.10***	0.13***	0.13***	0.22***	0.40***	0.61***
		(-112.56)	(-224.47)	(-29.16)	(90.10)	(180.53)	(176.57)	(154.94)	(270.00)	(254.83)
Patent family size	t-1	-0.01	0.01	0.01	0.01+	0.01***	0.01***	0.02***	0.03***	0.05***
		(-0.50)	(1.03)	(0.90)	(1.67)	(4.13)	(4.21)	(3.37)	(3.94)	(5.03)
Employees	t-1	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.04***	-0.04***	-0.04***	-0.04***
		(-4.89)	(-13.52)	(-12.87)	(-17.21)	(-26.19)	(-27.47)	(-14.78)	(-14.02)	(-8.83)
Patent count	t-1	0.77	0.77+	0.02	-0.34	-0.53**	-0.49*	-0.54	-0.91*	-1.05
		(0.78)	(1.94)	(0.06)	(-1.15)	(-2.60)	(-2.38)	(-1.33)	(-2.17)	(-1.58)
Originality index	t-1	14.90***	17.95***	19.93***	20.28***	20.66***	21.03***	21.26***	20.41***	19.06***
		(6.37)	(19.20)	(21.18)	(28.93)	(42.91)	(42.77)	(22.37)	(20.69)	(12.18)
Cult. Distance	t-1	-0.39	-0.74**	-1.14***	-1.22***	-1.34***	-1.52***	-1.44***	-1.35***	-1.58***
		(-0.57)	(-2.69)	(-4.10)	(-5.89)	(-9.42)	(-10.50)	(-5.13)	(-4.63)	(-3.42)
Constant		-3.20**	-2.41***	-2.62***	-2.47***	-1.81***	-0.78***	-0.21	0.78+	2.29**
		(-3.03)	(-5.70)	(-6.15)	(-7.79)	(-8.29)	(-3.49)	(-0.50)	(1.75)	(3.24)
Observations		7145	7145	7145	7145	7145	7145	7145	7145	7145

Year dummies are included in all regressions. As explained in our equations, all independent variables are in their first order lags.
z statistics in parentheses
$^{+}p<0.10$
$^{*}p<0.05$
$^{**}p<0.01$
$^{***}p<0.001$

of our second moderator variable reported in Table 5 (i.e. Coll. Distance x Cross-country), is also positive and increasing with the quantiles. Similarly, this result implies that the relationship between collaboration distance and firm performance can be moderated by a firm's decision to collaborate with inventors from another country. That is, firms engaging in cross-country collaborations tend to get a higher firm profitability in the subsequent year compared with those that do not engage with inventors from other countries. This finding rejects our final hypothesis, H3, and thus implies that the link between collaboration distance and firm performance is not weaker in companies that engage in cross-country collaboration networks compared with those that do not. This finding is consistent with several previous studies which argued that firms benefit from international collaborations by being exposed to a wider variety of knowledge sources (Ahuja, 2000; Cohen and Caner, 2016; Vasudeva et al., 2012).

Our regression results in Tables 3 to 5 also reveal other interesting findings concerning our control variables. For instance, the number of employees is negatively associated with profitability in the subsequent year in all quantiles. R&D intensity has a negative effect on firm profitability at lower quantiles (i.e., in companies with lower profitability levels) and positive in higher quantiles (i.e., in those companies with higher profitability levels). Our results also indicate that the number of patents in the previous year will have a negative impact on the current values of firm profitability in all our three models. Furthermore, our indicators for technological diversity and the quality of firm inventions, firm's originality index and patent family size, both have positive effects on firm profitability in all quantiles.

While Table 3 to 5 provide results of our estimations using the standard quantile regression, we also estimated the three models using simultaneous quantile regression with 100 bootstrap replications to ensure precision in our inference. Fig. 5 provides graphical representations of our simultaneous quantile regression results for our main variables (i.e., those used to test hypotheses H1 to H3). The first plot shows the quantile regression results for our main variable, (collaboration) distance in Equation 1 and the other two displayed the results of the interaction terms in Equation 2 and 3, respectively. Note, the first plot exhibits a steeper increasing pattern across the quantiles, starting from lower values at the lower quantiles and reaching relatively large positive values at the upper quantile. The second plot does not change much across the quantiles, although it tends to be increasing slightly (overall), while the third plot seems to decline as the quantile increases except at the highest quantile. Generally, these results are consistent with those reported in Table 3, 4 and 5. Further discussions on our results and their implications are provided in the conclusion.

5.3. Robustness

To ensure that our findings are robust, we have to eliminate several possible concerns with our data. First, the fact that both our moderator variables (interfirm and cross-country dummies in Equations 2 and 3) have significant coefficients (in Table 4 and 5 respectively) suggests that these variables have strong influences on profitability. Excluding influential variables such as these two on profitability in Equations 1 could, therefore, raise a concern on whether it could lead our initial analysis to omission bias[5]. Second, autocorrelation and heteroscedasticity could still be present within each of our quantile subsamples (Θ = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9). Autocorrelation and heteroscedasticity have been known to cause bias or inconsistent results. Third, the fact that the average firm profitability per year in our data falls steeply in 2007 (see Fig. A1 in the Appendix) and then fluctuates in the next 3 years (i.e., until 2010) is a sign of unstable firm growth. As explained previously, the sudden decline in profitability levels in 2007 followed by the unstable levels between 2008 and 2010 in our data are probably due to the great global recession in the late 2000s (Davis, 2009; World Economic Situation and Prospects, 2013). The scale and timing of the recession varied from country to country. In our sample, firm profitability (on average) seems to be affected from 2007 to 2010 (see Fig. 2a in the Appendix). This kind of financial shock affecting the trajectory of the outcome variable can cause bias in the analysis. And last, problems associated with endogeneity, which can also lead biased estimations, are common with panel data such as in our sample. Endogeneity is a condition in which some of the explanatory variables are correlated with the error term and is often a problem caused by measurement errors, variable omissions or reverse causality – which occurs when one (or several) of the explanatory variables also depends on the outcome variable. Reverse causality is one of the major concerns for studies dealing with innovation

[5] Note, we also run our quantile regression for Equation 1 with both moderator dummies included. The result for our main variable, collaboration distance, is still positive and significant. These results again support hypothesis H1. We also repeated our quantile regressions and used robust options to see if our previous results are affected by autocorrelation and heteroscedasticity (within each quantile subsample). The results are again similar.

Table 4
Quantile regression results for Model 2 in Equation 2 (Dependent variable = Firm Profitability).

	Lag	10%	20%	30%	40%	50%	60%	70%	80%	90%
Coll. Distance	t-1	1.26*	2.10***	2.19***	2.21***	2.50***	2.93***	2.94***	3.04***	3.66***
		(2.39)	(8.90)	(9.66)	(13.51)	(20.25)	(23.00)	(13.10)	(13.28)	(9.71)
R&D intensity	t-1	-0.33***	-0.32***	-0.02***	0.12***	0.14***	0.14***	0.24***	0.40***	0.61***
		(-93.37)	(-202.35)	(-10.80)	(111.94)	(165.33)	(159.22)	(161.47)	(263.50)	(241.71)
Patent family size	t-1	-0.00	0.01	0.01	0.01+	0.01**	0.02***	0.02**	0.02**	0.05***
		(-0.25)	(1.28)	(0.87)	(1.68)	(3.06)	(4.39)	(2.80)	(3.08)	(4.74)
Employees	t-1	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
		(-6.01)	(-14.23)	(-13.69)	(-18.33)	(-25.91)	(-26.92)	(-15.37)	(-15.01)	(-9.05)
Patent count	t-1	1.12	0.73	0.00	-0.55+	-0.55*	-0.55*	-0.91*	-1.24**	-1.09
		(1.10)	(1.60)	(0.01)	(-1.75)	(-2.30)	(-2.24)	(-2.09)	(-2.82)	(-1.50)
Originality index	t-1	19.19***	20.12***	22.10***	22.75***	22.53***	22.28***	22.92***	22.32***	21.26***
		(8.21)	(19.20)	(22.00)	(31.41)	(41.22)	(39.41)	(23.02)	(21.99)	(12.71)
Cult. Distance	t-1	-0.37	-1.04***	-1.15***	-1.24***	-1.29***	-1.57***	-1.42***	-1.46***	-1.67***
		(-0.54)	(-3.37)	(-3.89)	(-5.81)	(-8.04)	(-9.45)	(-4.85)	(-4.88)	(-3.38)
Interfirm	t-1	-40.23***	-35.73***	-31.77***	-29.37***	-27.80***	-25.73***	-20.10***	-16.71***	-11.75***
		(-10.86)	(-21.50)	(-19.94)	(-25.57)	(-32.09)	(-28.71)	(-12.74)	(-10.38)	(-4.43)
Cross-country	t-1	20.51**	20.09***	19.70***	17.21***	14.77***	12.68***	8.00*	5.01	-1.25
		(2.64)	(5.76)	(5.90)	(7.14)	(8.12)	(6.75)	(2.42)	(1.49)	(-0.22)
Interfirm x Coll. Distance	t-1	2.20**	1.57***	0.97**	0.70**	0.56**	0.35*	0.10	-0.22	-0.47
		(3.00)	(4.78)	(3.09)	(3.08)	(3.26)	(1.97)	(0.33)	(-0.69)	(-0.89)
Constants		14.55*	12.94***	8.96**	9.34***	11.24***	12.60***	12.00***	12.61***	15.41**
		(2.09)	(4.15)	(3.00)	(4.33)	(6.91)	(7.49)	(4.05)	(4.17)	(3.09)
Observations		7022	7022	7022	7022	7022	7022	7022	7022	7022

Year dummies are included in all regressions. As explained in our equations, all independent variables are in their first order lags.
z statistics in parentheses
$^{+}p < 0.10$
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

Table 5
Quantile regression results for Model 3 in Equation 3 (dependent variable = Firm Profitability).

	Lag	10%	20%	30%	40%	50%	60%	70%	80%	90%
Coll. Distance	t-1	1.26*	2.10***	2.19***	2.21***	2.50***	2.93***	2.94***	3.04***	3.66***
		(2.39)	(8.90)	(9.66)	(13.51)	(20.25)	(23.00)	(13.10)	(13.28)	(9.71)
R&D intensity	t-1	-0.33***	-0.32***	-0.02***	0.12***	0.14***	0.14***	0.24***	0.40***	0.61***
		(-93.37)	(-202.35)	(-10.80)	(111.94)	(165.33)	(159.22)	(161.47)	(263.50)	(241.71)
Patent family size	t-1	-0.00	0.01	0.01	0.01+	0.01**	0.02***	0.02**	0.02**	0.05***
		(-0.25)	(1.28)	(0.87)	(1.68)	(3.06)	(4.39)	(2.80)	(3.08)	(4.74)
Employees	t-1	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
		(-6.01)	(-14.23)	(-13.69)	(-18.33)	(-25.91)	(-26.92)	(-15.37)	(-15.01)	(-9.05)
Patent count	t-1	1.12	0.73	0.00	-0.55+	-0.55*	-0.55*	-0.91*	-1.24**	-1.09
		(1.10)	(1.60)	(0.01)	(-1.75)	(-2.30)	(-2.24)	(-2.09)	(-2.82)	(-1.50)
Originality index	t-1	19.19***	20.12***	22.10***	22.75***	22.53***	22.28***	22.92***	22.32***	21.26***
		(8.21)	(19.20)	(22.00)	(31.41)	(41.22)	(39.41)	(23.02)	(21.99)	(12.71)
Cult. Distance	t-1	-0.37	-1.04***	-1.15***	-1.24***	-1.29***	-1.57***	-1.42***	-1.46***	-1.67***
		(-0.54)	(-3.37)	(-3.89)	(-5.81)	(-8.04)	(-9.45)	(-4.85)	(-4.88)	(-3.38)
Interfirm	t-1	-40.23***	-35.73***	-31.77***	-29.37***	-27.80***	-25.73***	-20.10***	-16.71***	-11.75***
		(-10.86)	(-21.50)	(-19.94)	(-25.57)	(-32.09)	(-28.71)	(-12.74)	(-10.38)	(-4.43)
Cross-country	t-1	20.51**	20.09***	19.70***	17.21***	14.77***	12.68***	8.00*	5.01	-1.25
		(2.64)	(5.76)	(5.90)	(7.14)	(8.12)	(6.75)	(2.42)	(1.49)	(-0.22)
Interfirm x Coll. Distance	t-1	2.20**	1.57***	0.97**	0.70**	0.56**	0.35*	0.10	-0.22	-0.47
		(3.00)	(4.78)	(3.09)	(3.08)	(3.26)	(1.97)	(0.33)	(-0.69)	(-0.89)
Constants		14.55*	12.94***	8.96**	9.34***	11.24***	12.60***	12.00***	12.61***	15.41**
		(2.09)	(4.15)	(3.00)	(4.33)	(6.91)	(7.49)	(4.05)	(4.17)	(3.09)
Observations		7022	7022	7022	7022	7022	7022	7022	7022	7022

Year dummies are included in all regressions. As explained in our equations, all independent variables are in their first order lags.
z statistics in parentheses
$^{+}p < 0.10$
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

activities and performance, both at firm-level and country-level, as both factors often simultaneously influence one another (Cainelli et al., 2006; Coad and Rao, 2010), creating an endogeneity problem. We believe that endogeneity may exist in our panel data due to a possible reverse causality effect between firm profitability and some of our explanatory variables such as R&D intensity,

To check that our findings presented earlier are not affected by all of the aforementioned problems (or concerns), a robustness analysis is conducted. We re-estimated all three models in Equations 1-3 but using post-recession data only (i.e., observations between 2011 and 2016)[6] with a two-step system generalized method of moments (GMM) estimator (Blundell & Bond, 1998). The advantage of using post-recession data is that they are stable and unaffected by the great recession. On top of that, this restriction helps eliminate outliers in our data which are mostly observed between the 2007 to 2010 period. The system GMM, on the other hand, is well suited for panel data suspected of having heteroscedasticity, autocorrelation and endogeneity issues. It is known to be valid and consistent with dynamic[7] linear models that have such issues. System GMM is commonly used for country-level panel studies such as in autoregressive (AR) and autoregressive distributed lag (ADL) models (Alam et al., 2019; Cai et al., 2020; Siddiqui and Ahmed, 2013) and firm-level analysis (Song et al., 2018; Su and Moaniba, 2017). Another advantage of a system GMM estimator is its abilities to control for unobserved firm heterogeneity, known as firm fixed effects (Roodman, 2009). Unfortunately, system GMM is not designed for quantile regression hence we cannot verify our previous results for each specific quantile. However, we can still exploit our post-recession data with a two-step system GMM estimation to test our hypotheses 1-3 and see if our findings are consistent with those derived from the quantile regression results.

Our results for GMM estimations are reported in Table 6. The first and second columns show the results for Equation 1 (without moderator variables and with moderator variables, respectively). The coefficient for our main variable in these columns, distance, is significant and positive. Column 3 and 4 display the results for Equation 2 (with the first moderator variable only and with both moderator variables, respectively). The coefficient for our main variable in these columns, distance x interfirm, is again significant and positive. Lastly, the coefficient for the main variable in column 5 and 6, distance x cross-country, is also positive and significant. Note, columns 2, 4, and 6 are included to address the first concern that omitting moderator variables may lead to bias. However, as shown in these GMM results, our findings are similar to those reported in the previous subsections. That is, H1 and H2 are again supported while hypothesis H3 is again rejected (just as in Section 5.1 and 5.2).

6. Conclusion

This paper sheds lights on the relations between inventor collaboration, geographic distance and firm performance. Specifically, it examined the link between collaboration distance and firm profitability. Collaboration distance is our measure for the average geographic distance between inventors in a firm and their partners. In addition, the moderating roles of two types of inventor collaborations, interfirm (i.e., between different firms) and cross-country collaborations (i.e., between different countries), on the distance-profitability nexus are also explored. Existing literature on the determinants of firm performance in the innovation management and economics literature have focused mostly on the links between R&D spending and innovation, and R&D spending and geographic distance. Although literature has converged on the role of technological collaboration in innovation performance Giuliani et al., 2016), the relationship between geographic distance and firm growth is rarely investigated. The overall objective of this paper is twofold: ((1) to investigate the effect of geographic distance between collaborating inventors on firm performance, and (2) to explore the moderating roles of interfirm and cross-country collaboration networks on such effect.

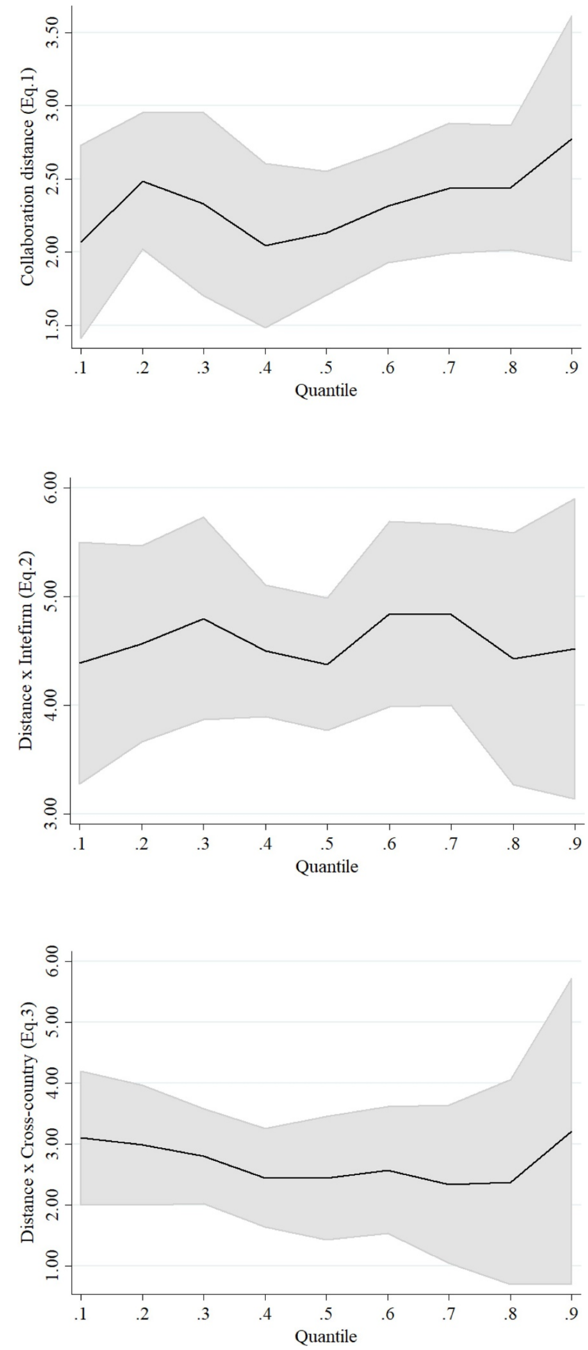


Fig. 5. The distribution of coefficients for our main variables across quantiles

There are several important empirical findings emerged from our study and are summarized as follows:

- First, in our main analysis, we found a strong link between collaboration distance and firm performance. In fact, our empirical results provide new evidence that the geographic distance between collaborating inventors has a positive causal effect on the profitability level of firms to which the inventors belong. This finding suggests that an increase in the average geographic distance between inventors would lead to higher profit margins in the companies the inventors work for. This finding is consistent with a number of past similar studies that highlighted the

[6] Note, pre-great recession data from our sample covers only three years, i.e. 2004-2006, which is too small for our analysis. For this reason, we turn to the post-recession data instead for our robustness analysis.

[7] To make sure autocorrelation is dealt with accordingly by our system GMM, a first order lagged dependent variable is inserted into Equations 1-3 as the independent variable. By doing this, our three models become dynamic and autoregressive in nature.

[8] Since patents family size values are observed to be quite constant even when patents count changes significantly. This behavior suggests that patents family size is not influenced by the simultaneous causal-relationship between patents count and firm profitability, which is the suspected cause of endogeneity in our models Eq. 1-(3).

Table 6
Two-step system GMM results (dependent variable = Firm Profitability).

	Lag	(1)	(2)	(3)	(4)	(5)
Profitability	t-1	0.51***	0.56***	0.61***	0.59***	0.62***
		(12.00)	(17.84)	(28.00)	(26.55)	(29.58)
Employees	t-1	-0.00	-0.00	0.00	0.00	0.00
		(-0.24)	(-0.45)	(0.29)	(0.19)	(0.08)
R&D intensity	t-1	0.00	0.02	0.11**	0.11**	0.13***
		(0.00)	(0.34)	(3.00)	(3.06)	(4.00)
Patent count	t-1	0.75	0.47	0.16	0.11	0.12
		(1.60)	(1.40)	(0.57)	(0.38)	(0.41)
Originality index	t-1	4.71*	3.27*	3.48**	3.56**	3.97**
		(2.12)	(2.04)	(2.73)	(2.79)	(3.22)
Cult. Distance	t-1	-0.08	0.01	0.12	0.26	0.16
		(-0.24)	(0.03)	(0.50)	(1.06)	(0.68)
Coll. Distance	t-1	0.48*	0.35+	-0.01	-0.01	-0.04
		(2.04)	(1.66)	(-0.04)	(-0.04)	(-0.25)
Patent family size	t-1	-0.05	0.02	0.03	0.04	-0.00
		(-0.80)	(0.33)	(0.81)	(1.15)	(-0.12)
Interfirm	t-1		-1.15*	-1.39**	-0.90*	-0.96*
			(-2.48)	(-3.25)	(-2.08)	(-2.16)
Cross-country	t-1		-12.75*	-12.01**	-17.87**	-15.94**
			(-2.57)	(-2.59)	(-3.23)	(-2.99)
Interfirm x Coll. Distance	t-1			0.65*		-0.17
				(2.07)		(-0.42)
Cross-country x Coll. Distance	t-1				0.97**	1.19*
					(2.64)	(2.57)
Constant		2.98*	16.61***	14.34**	19.72***	0.00
		(2.47)	(3.41)	(3.11)	(3.59)	(.)
Observations		2608	2452	2452	2452	2452

Note: As explained in our equations, all independent variables are in their first order lags. The first order lag of the dependent variable is now included among the independent variables to capture the effect of autocorrelation. All explanatory variables are treated as endogenous (except Patents family size)[8] and are instrumented with lags between 1 and 3. The pre-determined regressor (the lagged dependent variable) is instrumented with its second lag. Year dummies are included in all regressions. As explained in our equations, all independent variables are in their first order lags.
^{z}statistics in parentheses
$^{+}p<0.10$
$^{*}p<0.05$
$^{**}p<0.01$
$^{***}p<0.001$

positive relationship between geographic distance and firm performance (Berchicci et al., 2016; Zhang et al., 2020) – although they looked at the phenomenon from different perspectives and with different sets of analytical approaches.

- Moreover, our key results are particularly consistent with findings of another empirical study which emphasized that this type of relationship (between collaboration distance and firm performance) is especially true for firms located in highly developed regions (Qiu et al., 2017). This is because, for reasons explained earlier, firms in our sample are picked from a list of highly innovative and top R&D intensive firms which all come from highly developed regions including the US, Japan and Europe.
- Furthermore, when interpreted in terms of knowledge value and from the lens of knowledge search strategies, this key finding from our study seems to support the old maxim that long-distance collaborations allow firms to acquire totally different sets of knowledge and skills from those available locally. As a result, they would come up new inventions or products from utilizing such outside knowledge; and in turn improve their financial performance (Darroch, 2005; Decarolis and Deeds, 1999). In addition, prior studies have argued that knowledge acquired through distant collaborations have higher commercial value, degree of diversity and novelty (e.g., Capaldo & Messeni Petruzzelli, 2015). Therefore, our present study validates their findings by providing new empirical evidence indicating that knowledge acquired from distant sources can actually be translated into higher firm profitability.
- We could also interpret our main finding, as another statistical evidence supporting the increasingly popular notion that technological breakthroughs in communication systems over the last few decades have significantly led to more benefits to firms – such as increase in productivity due to distant collaborations and reduced communication costs across larger geographic distances. However, actual empirical investigation into this premise should be undertaken.
- Second, our study finds that the positive causal effect of geographic distance between collaborating inventors on firm performance can be moderated by two types of collaboration networks.
  a First, in an interfirm network (i.e., firm-level from a business perspective), firm inventors may either choose to collaborate among themselves in an intra-firm collaboration (usually across different locations as in a multinational corporation) or with inventors from other companies in an interfirm collaboration. Our results suggest that engaging with other firms (i.e., an interfirm collaboration) can increase the positive effect of collaboration distance on firm profitability. In other words, as the geographic distance between collaborating inventors increases, the profitability level of the firm (to which the leading inventor belongs) will also increase. This effect increases further if the firm (which collaborating inventors belong to) start to collaborate with other firms. This finding could interpreted in a situation such as this. Suppose inventor Y, who works for firm 1, has two potential innovation partners to choose from whom are located roughly the same physical distance away from him/her. One option, inventor 2, happens to work for the same firm 1 but in a different location. Option two, inventor 3, works for a different firm 2. According to our research finding, a collaboration between inventor 1 and 3 (from different firms i.e., an interfirm collaboration) should bring more financial benefits to firm 1 compared with a collaboration between inventor 1 and 2 (both from the same firm i.e., an intra firm collaboration).
  b Second, in a cross-country network, inventors from a firm in a given country may collaborate with others within the same country (an intra-country collaboration) or with inventors from other countries (a cross-country collaboration). Our findings suggest that the positive (causal) effect of collaboration distance on firm profitability will increase further if the collaboration involves co-inventors from more than one country. This finding reflects the fact that different types of collaborations have their own advantages and disadvantages, especially across geographic boundaries. On the one hand, reduced costs and high productivity are some of the benefits of a collaboration across countries, while on the other hand vulnerability to cultural differences, language barrier, and political restrictions in countries are among the disadvantages of a collaboration over (long) distance. Our study, therefore provides new empirical evidence that, financially, benefits from long distance collaborations outweigh the costs – in the context of a firm innovation-performance nexus.

6.1. Contribution to theory and managerial implication

Our research paper contributes to literature on the management and economics of innovation in several ways.

- First, it extends the innovation strategy literature on the relationship between strategic alliance and firm growth by providing empirical evidence that the geographic distance between collaborating inventors has a positive and significant causal effect on firm performance. Our study finds that firms engaged in longer-distance inventor collaborations tend to show signs of higher profitability levels in the subsequent year compared with those that did not. An important managerial implication derived from this finding is to encourage firms to engage in longer distance inventor collaborations.
- Second, the fact that the positive causal effect of collaboration distance on firm performance can be moderated by two types of collaboration networks, the second key finding of this study, provides other important managerial implications. A positive moderating effect of interfirm

collaboration implies that firms should motivate their employees (i.e., inventors) to engage more with inventors from other companies when it comes to long distance collaborations. Likewise, the paper also presents evidence on how cross-country collaboration can positively influence the causal effect of collaboration distance on firm performance. An implication from this finding is that firms should encourage their employees to collaborate more with inventors from other countries. Specifically, when it comes to choosing between two potential partners that are both located roughly the same distance from the inventor, where one of them is from the same firm while the other is from another firm, we argue (based on our finding) that the inventor from another firm is a better choice – indicated by the positive “interfirm” moderating effect. On the other hand, when choosing between potential inventor partners that are located around the same distance from a given inventor, the one on the other side of the national border is recommended – as reflected by the positive “cross-country” moderating effect.

- Third, a novel approach to constructing a firm-level indicator of the distance per yearly basis is introduced. This indicator is computed based on the longitudes and latitudes of the cities of inventors and patent data. Although the approach has been used in previous studies, to our knowledge, this is the first time it is adopted in the context of inventor distance. The procedure should allow researchers to easily track the trajectories and dynamics of inventor collaboration across spatial distance.

6.2. Limitations and future research directions

Our study has some limitations. First, due to data unavailability, we cannot control for some major drivers of firm performance such as the size of the market demands and employee qualifications. Second, despite the use of patent data in measuring innovation activities in many innovation management and economics studies, it represents only a fraction of the actual intensity of innovation. Hence, the results for our variables that are constructed from patent data such as the collaboration distance could be underestimated. Second, while co-invention is commonly used as a quantitative measure for international technical cooperation, it is occasionally criticized for its inability to fully reflect cross-border knowledge-intensive collaboration. Therefore, by using the number of inventors per patent in the construction of our moderator variables, we could have underestimated the actual magnitudes of the moderating effects on a distance-performance relationship.

Based on some of the key findings of this study, there are several potential research topics that could be investigated in the future. These include the following: 1) examining how the moderator variables in this study could also moderate the effect of R&D expenditure on firm performance; 2) expanding the study to examine how the sophisticated and co-evolutionary dynamics of R&D expenditure and collaboration distance, and how they jointly affect firm performance; and 3) narrowing down the scope to selected technology industries or geographical regions.

CRediT authorship contribution statement

Igam M. Moaniba: Investigation, Data curation, Formal analysis, Software, Visualization, Writing - original draft, Writing - review & editing. **Hsin-Ning Su:** Funding acquisition, Investigation, Methodology, Writing - original draft, Supervision, Writing - review & editing. **Pei-Chun Lee:** Conceptualization, Investigation, Project administration, Resources, Writing - original draft, Validation, Writing - review & editing.

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Appendix

Appendix A

Table A1
Descriptive statistics.

	Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
1	Profitability	Annual firm revenue to sales ratio	7,228	5.415345	138.0595	-10,400	169.42
2	Collaboration distance	Yearly average inventor geographic distance per firm patent (1000 km)	7,145	0.674777	0.786563	0	16.01
3	R&D intensity	Annual firm R&D expense to sales ratio	7,228	9.991588	91.2088	0	6311
4	Employees	No. of firm employees per year (in 1000 units)	7,228	39.97697	62.95488	0	610.08
5	Patents count	No. of patents per firm per year (in 1000 units)	7,228	0.152012	0.390184	0	9.18
6	Originality index	Firm's originality index per year	7,145	0.410569	0.140695	0	0.94
7	Patents family size	Firm patent family size per year	7,145	12.16892	23.62085	1	572.69
8	Cultural distance	Yearly average cultural distance between firm inventor and partners	7,145	0.4186	0.618743	0	9.14
9	Inventors	Yearly average no. of inventors per firm patent	7,145	2.911964	0.973881	1	16.75
10	Assignees	Yearly average no. of assignees per firm patent	7,145	1.035442	0.104561	1	4
11	Assignee countries	Yearly average no. of assignee countries per firm patent	7,145	1.009586	0.056506	1	2

Table A2
Correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Profitability	1.00											
2	Collaboration distance	0.01	1.00										
3	R&D intensity	-0.13***	0.02*	1.00									
4	Employees	0.01	-0.01	-0.03***	1.00								
5	Patents count	0.01	0.01	-0.01	0.51***	1.00							
6	Originality index	-0.01	0.07***	0.03**	-0.05***	-0.09***	1.00						
7	Patents family size	-0.02	0.06***	0.07***	-0.04***	-0.02*	0.14***	1.00					
8	Cultural distance	0.01	0.65***	0.01	0.02	-0.01	-0.00	0.03**	1.00				
9	Interfirm	-0.01	-0.04***	-0.00	0.29***	0.28***	-0.16***	-0.01	-0.01	1.00			
10	Cross-country	0.01	0.07***	-0.01	0.34***	0.34***	-0.07***	0.02*	0.11***	0.62***	1.00		
11	Distance x Interfirm	0.01	0.37***	0.01	0.17***	0.18***	-0.03***	0.06***	0.31***	0.61***	0.54***	1.00	
12	Distance x Cross-country	0.01	0.31***	0.01	0.18***	0.20***	-0.04***	0.06***	0.28***	0.45***	0.73***	0.81***	1.00

Note: *, **, and ***indicate significance at 0.1, 0.05, and 0.01 levels, respectively. All variables (except profitability) are in their first order lags.

Table A3
Descriptive statistics for profitability in each of the 10 quantile groups.

Quantile group	Obs.	Mean	Std. Dev.	Min	Max
1	760	-45.33	421.21	-10,400.00	0.00
2	575	1.94	0.87	0.00021	3.20
3	667	4.26	0.59	3.20	5.23
4	667	6.18	0.52	5.24	7.08
5	667	8.01	0.54	7.08	8.95
6	668	9.95	0.58	8.95	11.01
7	667	12.30	0.76	11.02	13.58
8	667	15.28	1.03	13.58	17.15
9	667	19.73	1.55	17.16	22.70
10	667	29.98	9.85	22.71	169.42

Note: 1) The total number of observations for profitability in this table is 6672 which is 556 less than the 7228 observations for profitability in Table A1. This occurs because we relate profitability to all 1-year lagged independent variables in our quantile regression models in Equation 1-3 – meaning that the latest year (2016) has to be discarded in the regressions, 2) All mean, std. dev, min and max values are rounded off to 2 decimal places except for the min value of quantile group 2.

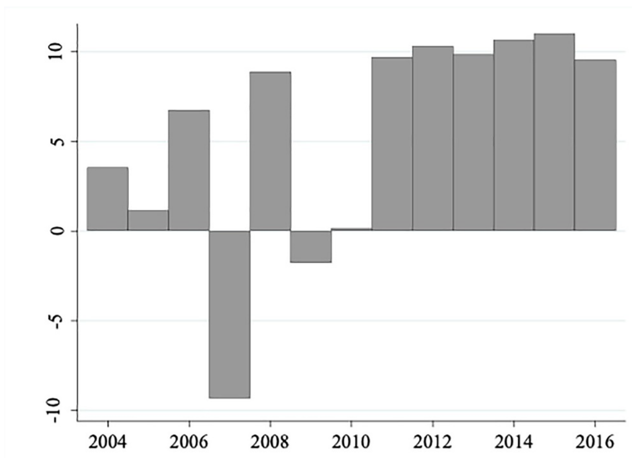

Fig. A1. The average firm profitability for 556 firms between 2004 and 2016

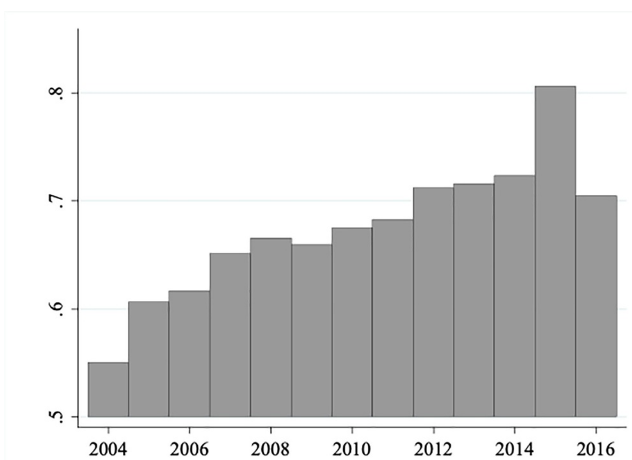

Fig. A2. The average collaboration distance for the 556 firms between 2004 and 2016.

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